

An Effective Characterization of Schur-Convex Functions with Applications

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An effective necessary and sufficient condition for S-convexity is presented and applications are given.

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1. Introduction and summary

In his paper concerning Hadamard's inequality Schur [7] introduced and characterized a class of functions which were later called Schur-convex or simply S-convex. This characterization was completed by Ostrowski [6]. Hardy, Littlewood and Pólya attached importance to these functions in presenting and proving many results in their book [3], while Marshall and Olkin [5] used the S-functions as a key in creating an unified theory of inequalities.

Both Schur and Ostrowski characterized the S-functions in terms of their differential coefficients. Some further results described relations between S-convexity and convexity (in the sense of Jensen). Among others, it is now well known, that any symmetric convex function is S-convex, but not vice versa.

The aim of this paper is to present a simple and effective characterization of S-convexity. As we will see, this characterization leads directly to some known and unknown results in this subject. Applications of the characterization are also provided.

2. Definitions and main result

Let us consider a subset \mathcal{A} of the real euclidean space R^n , where $n > 1$. Any element of \mathcal{A} will be presented as a row-vector $x = (x_1, \dots, x_n)$. The set \mathcal{A} is said to be *symmetric* if $(x_1, \dots, x_n) \in \mathcal{A}$ implies that $(x_{i_1}, \dots, x_{i_n}) \in \mathcal{A}$ for any permutation x_{i_1}, \dots, x_{i_n} of the numbers x_1, \dots, x_n . Moreover, a real function φ on a symmetric set \mathcal{A} is said to be *symmetric*, if $\varphi(x_1, \dots, x_n) = \varphi(x_{i_1}, \dots, x_{i_n})$. We say that a vector y in a symmetric set

$\mathcal{A} \subseteq R^n$ majorizes $x \in \mathcal{A}$, and write $x \prec y$, if

$$\begin{aligned} & \max\left\{\sum_{j=1}^k x_{i_j} : 1 \leq i_1 < i_2 < \dots < i_k \leq n\right\} \\ & \leq \max\left\{\sum_{j=1}^k y_{i_j} : 1 \leq i_1 < i_2 < \dots < i_k \leq n\right\} \text{ for } k = 1, \dots, n-1 \\ & \text{and } \sum_{i=1}^n x_i = \sum_{i=1}^n y_i. \end{aligned}$$

The relation \prec possesses the usual properties of preordering, i.e.

- (*) $x \prec x$ for any $x \in \mathcal{A}$,
- (**) if $x \prec y$ and $y \prec z$ then $x \prec z$ for all $x, y, z \in \mathcal{A}$.

A real function φ on a convex set $\mathcal{A} \subseteq R^n$ is said to be *convex* if

$$\varphi(\lambda x + (1 - \lambda)y) \leq \lambda\varphi(x) + (1 - \lambda)\varphi(y) \text{ for any } x, y \in \mathcal{A} \text{ and } \lambda \in (0, 1). \tag{1}$$

Let us mention (cf. [3]) that any continuous function φ on a convex set \mathcal{A} is convex, if and only if,

$$\varphi\left(\frac{x + y}{2}\right) \leq \frac{1}{2}[\varphi(x) + \varphi(y)] \text{ for any } x, y \in \mathcal{A}. \tag{2}$$

The following lemma will be useful in Section 3.

Lemma 2.1 (cf. [5], **Proposition 16.B.7**). *Let f be a convex function on a convex set \mathcal{A} and g be a nondecreasing convex function on R . Then the composition $\phi(x) = g(f(x))$ is convex on \mathcal{A} . Moreover, if f is strictly convex and g is increasing strictly convex then ϕ is strictly convex.*

Proof. By definition of ϕ , $\phi(\lambda x + (1 - \lambda)y) = g(f(\lambda x + (1 - \lambda)y))$. Since f is convex and g is nondecreasing, we get $g(f(\lambda x + (1 - \lambda)y)) \leq g(\lambda f(x) + (1 - \lambda)f(y))$. Now the desired result follows by the convexity of g . □

Definition 2.2. A real function φ on a symmetric set \mathcal{A} is said to be Schur-convex (or simply S-convex) if it is isotonic relative to the preordering \prec , that is, if $x \prec y$ implies $\varphi(x) \leq \varphi(y)$ for any $x, y \in \mathcal{A}$. The function φ is said to be strictly S-convex if the strict inequality $\varphi(x) < \varphi(y)$ does hold for any pair $x, y \in \mathcal{A}$, such that $x \prec y$ but y can not be obtained from x by permutation of its components.

Remark 2.3. By definition of the preordering \prec , any function ϕ is (strictly) S-convex, if and only if, for arbitrary real functions g and h , such that g is positive, the function $g(\sum_{i=1}^n x_i)\phi(x) + h(\sum_{i=1}^n x_i)$ is (strictly) S-convex. Hence, S-convex function may not be continuous, or even measurable.

It is well known (cf. [6, 7]) that a continuously differentiable function φ defined on the cartesian product I^n of an open interval $I \subseteq R$ is S-convex, if and only if,

- (a) $\varphi(x) = \varphi(x_1, \dots, x_n)$ is a symmetric, and,
- (b) $(x_i - x_j)(\varphi_{(i)}(x) - \varphi_{(j)}(x)) \geq 0$ for all $x \in I^n$, where $\varphi_{(k)}(x) = \frac{\partial \varphi(x)}{\partial x_k}$.

It is also known, that any symmetric convex function φ defined on a symmetric convex set \mathcal{A} in R^n is S-convex (see [7], or [5]).

We shall prove the following

Theorem 2.4. *Let φ be any function defined on a symmetric convex set \mathcal{A} in R^n . Then*

- (A) *The function φ is S-convex if and only if*
 - (i) $\forall (x_1, \dots, x_n) \in \mathcal{A}, \forall 1 \leq i < j \leq n, \varphi(x_1, \dots, x_{i-1}, x_i, x_{i+1}, \dots, x_{j-1}, x_j, x_{j+1}, \dots, x_n) = \varphi(x_1, \dots, x_{i-1}, x_j, x_{i+1}, \dots, x_{j-1}, x_i, x_{j+1}, \dots, x_n)$, and
 - (ii) $\forall (x_1, \dots, x_n) \in \mathcal{A}, \forall 0 < \lambda < 1, \varphi(\lambda x_1 + (1 - \lambda)x_2, \lambda x_2 + (1 - \lambda)x_1, x_3, \dots, x_n) \leq \varphi(x_1, \dots, x_n)$.
- (B) *The function φ is strictly S-convex if and only if it satisfies the conditions (i) and (ii) with the strict inequality $<$ instead of \leq for all $(x_1, \dots, x_n) \in \mathcal{A}$ such that $x_1 \neq x_2$.*

Remark 2.5. The condition (i) is equivalent to symmetry of φ , while (ii) is weaker than either convexity or quasiconvexity (see [5], Sec. 3.C, for definition).

Proof. Part (A). Necessity of the conditions (i) and (ii).

Necessity of (i) is evident. To show the necessity of (ii) we note that $(\lambda x_1 + (1 - \lambda)x_2, \lambda x_2 + (1 - \lambda)x_1, x_3, \dots, x_n) = xT$, where

$$T = \begin{bmatrix} \lambda & 1 - \lambda & 0 & 0 & \dots & 0 \\ 1 - \lambda & \lambda & 0 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 1 \end{bmatrix}.$$

Since T is a doubly stochastic matrix, we get $xT \prec x$ (cf. [5], Th. 2.A.4). Now the necessity of (ii) follows by definition of S-convexity.

Sufficiency of (i) and (ii). Let x and y be arbitrary vectors in \mathcal{A} such that $x \prec y$. Then, by Theorem of Muirhead (see [3], or [5], Lemma 2.B.1) there exist matrices $T_k, k = 1, \dots, n - 1$, such that $x = yT_1T_2\dots T_{n-1}$, while each T_k may be rewritten in the form (t_{ij}) with

$$t_{ij} = \begin{cases} \lambda & \text{if either } i = j = r \text{ or } i = j = s, \\ 1 & \text{if } i = j \neq r, s, \\ 1 - \lambda & \text{if either } i = r \text{ and } j = s \text{ or } i = s \text{ and } j = r, \\ 0 & \text{otherwise,} \end{cases}$$

where $r = r(k)$ and $s = s(k)$ are positive integers not greater than n and $\lambda = \lambda(k)$ belongs to the interval $(0, 1)$. Let us define vectors $y^{(k)}, k = 0, 1, \dots, n - 1$, by setting $y^{(0)} = y$ and $y^{(k)} = y^{(k-1)}T_k$ for $k = 1, \dots, n - 1$. To see that $\varphi(x) \leq \varphi(y)$ we only need to notice that the conditions (i) and (ii) imply $\varphi(y^{(k)}) \leq \varphi(y^{(k-1)})$ for $k = 1, \dots, n - 1$.

The part (B) of this Theorem may be proved in the same way. □

From Theorem 2.4 we get the following corollaries.

Corollary 2.6 (Schur [7], Marshall and Olkin [5], Th. 3.C.2). Any symmetric convex function defined on a symmetric convex set \mathcal{A} is S -convex.

Corollary 2.7 (Marshall and Olkin [5], Th. 3.C.3). If φ is a symmetric function defined on a symmetric convex set \mathcal{A} in R^n satisfying the condition $\varphi(\lambda x + (1 - \lambda)y) \leq \max\{\varphi(x), \varphi(y)\}$ for all $\lambda \in (0, 1)$ and for all $x, y \in \mathcal{A}$ then φ is S -convex.

3. Further results and applications

We shall start from some auxiliary results.

Lemma 3.1. Any real measurable function f defined on an open interval I in R is convex, if and only if,

$$f(\lambda x + (1 - \lambda)y) + f(\lambda y + (1 - \lambda)x) \leq f(x) + f(y) \text{ for any } x, y \in I \text{ and } \lambda \in (0, 1). \quad (3)$$

Moreover, f is strictly convex, if and only if, the inequality in (3) is strict.

Proof. For necessity we shall use the fact that any measurable convex function φ on an open interval $I \subseteq R$ is continuous (cf. [4]). Let us recall that, in this case, the conditions (1) and (2) are equivalent. Thus, if f is convex, then by (1), $f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$ and $f(\lambda y + (1 - \lambda)x) \leq \lambda f(y) + (1 - \lambda)f(x)$ for $x, y \in I$ and $\lambda \in (0, 1)$. This implies (3). Conversely, by setting in (3) $\lambda = \frac{1}{2}$ we get (2). \square

Remark 3.2. By Bernstein-Doetsch Theorem (see [1]) the word "measurable" in Lemma 3.1 and throughout this section may be replaced by "locally bounded".

The following lemma is a direct consequence of Theorem 2.4 and Lemma 3.1.

Lemma 3.3 (Propositions 3.C.1 and 3.C.1.c in [5]). For a given measurable function f on an open interval $I \subseteq R$ the following are equivalent:

- (a) The function f is (strictly) convex on I .
- (b) The function $\varphi(x) = \sum_{i=1}^n f(x_i)$ is (strictly) S -convex on I^n .

Taking into account Remark 2.3, one can state the following theorem.

Theorem 3.4. For arbitrary real functions f, g and h on an open interval $I \subseteq R$, such that g is positive and f is measurable, the following are equivalent:

- (a) The function f is (strictly) convex,
- (b) The function $\phi_n(x_1, \dots, x_n) = g(\sum_{i=1}^n x_i) \sum_{i=1}^n f(x_i) + h(\sum_{i=1}^n x_i)$ is (strictly) S -convex.

Now, for a given f , let us consider the function $\psi_n(x) = \prod_{i=1}^n f(x_i)$. To state a necessary and sufficient condition for the S -convexity of ψ_n we need some notion.

A positive function f on an interval $I \subseteq R$ is said to be *logconvex* if $\ln f$ is convex.

Remark 3.5. We note that f is logconvex, if and only if, $\log_a f$ is convex for some $a > 1$. Moreover, by Lemma 2.1, any logconvex function is convex. However, a convex function may not be logconvex. For instance, the function $f(x) = x^2$ is convex, while $\ln f(x) = 2 \ln x$ is concave.

The following theorem is an extension of Proposition 3.E.1 in [5].

Theorem 3.6. For arbitrary real functions f, g and h on an open interval $I \subseteq R$, such that g is positive and f is measurable and positive, the following are equivalent:

- (a) The function f is (strictly) logconvex,
- (b) The function $\psi_n(x_1, \dots, x_n) = g(\sum_{i=1}^n x_i) \prod_{i=1}^n f(x_i) + h(\sum_{i=1}^n x_i)$ is (strictly) S-convex.

Proof. By Remark 2.3, we only need to consider the case $\psi_n(x) = \prod_{i=1}^n f(x_i)$. Since g is positive, the condition (ii) in Theorem 2.4 may be equivalently replaced by $\psi_2(\lambda x + (1 - \lambda)y), \lambda y + (1 - \lambda)x \leq \psi_2(x) + \psi_2(y)$, and, by definition of ψ_n , the last one reduces to $\ln f(\lambda x + (1 - \lambda)y) + \ln f(\lambda y + (1 - \lambda)x) \leq \ln f(x) + \ln f(y)$. Now the desired result follows from Theorem 3.4. □

Let us present some applications of Theorems 3.4 and 3.6.

Example 3.7. In descriptive statistics the ratio $v = \frac{s}{\bar{x}}$, where $\bar{x} = \frac{1}{n} \sum x_i$ and $s = \sqrt{\frac{1}{n-1} \sum (x_i - \bar{x})^2}$, is said to be the variation coefficient in the sample $x = (x_1, \dots, x_n)$, providing $\bar{x} \neq 0$. In general, the set of possible values of v is not bounded, but if x_1, \dots, x_n are nonnegative and $\sum x_i > 0$, then it is so. One can suspect that, under this additional condition, the coefficient v is normalized, in the sense that $0 \leq v \leq 1$. We shall show that this conjecture is false.

Given \bar{x} the function $s^2(x)$ may be presented in the form $s^2(x) = \frac{1}{n-1}(\varphi_n(x) - n\bar{x}^2)$, where $\varphi_n(x) = \sum x_i^2$. Thus, by Theorem 3.4, $s^2(x)$ is S-convex. Therefore, its maximal value is attained for the maximal element in the set

$$A = \left\{ (x_1, \dots, x_n) : x_i \geq 0, \sum x_i = n\bar{x} \right\}$$

with respect to the ordering \prec . It is well known that this element is $y = (0, \dots, 0, n\bar{x})$, and hence $\max_{x \in A} s^2(x) = s^2(y) = \frac{1}{n-1}(\sum y_i^2 - n\bar{x}^2) = n\bar{x}^2$. Therefore, the function v is not normalized but $\frac{v}{\sqrt{n}}$ is so.

Example 3.8. Any quadratic form of $x = (x_1, \dots, x_n)$ may be expressed as $\phi(x) = xAx^T$, where A is a symmetric matrix of $n \times n$. It is evident that such a function is symmetric, if and only if, $A = aI + b\mathbf{1}$, $a, b \in R$, where $\mathbf{1}$ is $n \times n$ matrix of ones. Thus, in this case, $xAx^T = a \sum x_i^2 + b(\sum x_i)^2$. Hence, by Theorem 3.4, a quadratic form $\phi(x) = xAx^T$ is S-convex, if and only if, $A = aI + b\mathbf{1}$ with $a \geq 0$, and strictly S-convex, if and only if, $a > 0$.

Example 3.9. Let us consider the function $\psi(x) = g(\sum x_i)e^{xAx^T} + h(\sum x_i)$, where $x = (x_1, \dots, x_n)$, while g and h satisfy the assumptions of Theorem 3.6. We are seeking for a necessary and sufficient condition to ψ be S-convex. It follows from Example 3.8, via Remark 2.3, that a necessary one is $A = aI + b\mathbf{1}$ with $a \geq 0$. To show its sufficiency, we only need to set in Theorem 3.6 $f(x) = e^{ax}$. Similarly, ψ is strictly S-convex, if and only if, $a > 0$.

Some interesting applications of Schur-convex functions in statistics can be found in [8] and [9].

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