

## On Statistical Limit Superior, Limit Inferior and Statistical Monotonicity

**Sumita Gulati**

*Assistant Professor of Mathematics S. A. Jain College, Ambala City (Haryana)*

**Mini**

*Assistant Professor of Mathematics S. A. Jain College, Ambala City (Haryana)*

### Abstract

The purpose of this paper is to study the statistical limit superior and inferior following the concept of statistical convergence and statistical cluster point of a sequence. We also study definition of statistically monotonicity and some of its properties.

**Keywords:** statistical convergence, statistically limit point, statistically cluster point, statistically limit superior, statistically limit inferior, statistically monotonicity, dense subsequence.

### Introduction

The concept of limit and cluster point of a sequence  $x$  have been extended to statistical limit and statistical limit points and cluster points [7], [8], [9] using the concept of natural density  $\delta$  [11] of a set  $A$  of positive integers. Statistical convergence has many applications in different fields of mathematics like number theory [6], summability theory [10] and in locally convex spaces [16].

Let  $A$  be a subset of  $\mathbb{N}$  and  $A(n) = \{a \in A : a \leq n\}$  then the natural density of  $A$ , denoted by  $\delta(A)$ , is defined by

$$\delta(A) = \lim_{n \rightarrow \infty} \frac{1}{n} |A(n)|$$

If the limit exists and where the vertical bars denotes the cardinality of enclosed set. A real or complex valued sequence  $x = \{\xi_n\}$  is said to converge stastically to the number  $\xi$ , if for every  $\varepsilon > 0$ , the set  $A_\varepsilon$  has density zero where  $A_\varepsilon = \{n \in \mathbb{N} : |\xi_n - \xi| \geq \varepsilon\}$  and it is denoted by  $\text{st-lim } x = \xi$ .

The number  $v$  is called a statistical cluster point of  $x = \{\xi_k\}$  if for every  $\varepsilon > 0$  the set  $\{k : |\xi_k - v| < \varepsilon\}$  does not have density zero.

Throughout in this paper  $\mathbb{N}$  and  $\mathbb{R}$  will denote the set of natural numbers and real numbers respectively and we will consider real number sequences.

Statistical Limit Superior And Statistical Limit Inferior:

In this section we study definitions of the concepts of statistical limit superior and inferior and to develop some stastical analogues of properties of the ordinary limit superior and inferior.

If  $k \subseteq \mathbb{N}$ , then  $k_n = \{k: k \leq n\}$  and  $|k_n|$  denotes the cardinality of  $k_n$ . For a real sequence  $x$  let  $B_x$  denote the set

$$B_x = \{b \in \mathbb{R}: \delta(k: \xi_k > b) \neq 0\}$$

$$\text{Similarly, } A_x = \{a \in \mathbb{R}: \delta(k: \xi_k < a) \neq 0\}$$

Note that throughout in this paper  $\delta(k) \neq 0$  means that either  $\delta(k) > 0$  or  $k$  does not have natural density.

**Definition:** If  $x$  is a real number sequence, then the statistical limit superior of  $x$  is given by

$$\text{St-lim sup } x = \begin{cases} \sup B_x, & \text{if } B_x \neq \emptyset, \\ -\infty, & \text{if } B_x = \emptyset. \end{cases}$$

Also, the statistical limit inferior of  $x$  is given by

$$\text{St-lim inf } x = \begin{cases} \inf A_x, & \text{if } A_x \neq \emptyset, \\ +\infty, & \text{if } A_x = \emptyset. \end{cases}$$

Following example will help to illustrate the above defined concept. Let us consider a sequence  $x = \{\xi_k\}$  defined by

$$\xi_k = \begin{cases} k, & \text{if } k \text{ is an odd square,} \\ 2, & \text{if } k \text{ is an even square,} \\ 1, & \text{if } k \text{ is an odd nonsquare,} \\ 0, & \text{if } k \text{ is an even nonsquare.} \end{cases}$$

Although  $x$  is unbounded above, it is “statistically bounded” because the set of squares have density zero.

Thus  $B_x = (-\infty, 1)$  and  $\text{st-lim sup } x = 1$ . Also,  $x$  is not statistically convergent since it has two (disjoint) subsequences of positive density that converge to 0 and 1, respectively (see [8]). Also note that the set of statistically cluster points of  $x$  is  $\{0, 1\}$ , and  $\text{st-lim sup } x$  equals the greatest element while  $\text{st-lim inf } x$  is the least element of this set. This observation leads to the main idea of the following theorem which can be proved by least upper bound argument.

**Theorem 1:** If  $\beta = \text{st-lim sup } x$  is finite, then for every positive number  $\varepsilon$

$$\delta\{k: \xi_k > \beta - \varepsilon\} \neq 0 \text{ and } \delta\{k: \xi_k > \beta + \varepsilon\} = 0.$$

Conversely, if (1) holds for every positive  $\varepsilon$  then  $\beta = \text{st-lim sup } x$ .

The dual statement for  $\text{st-lim inf } x$  is as follows.

**Theorem 2:** If  $\alpha = \text{st-lim inf } x$  is finite, then for every positive number  $\varepsilon$

$$\delta\{k: \xi_k < \alpha + \varepsilon\} \neq 0 \text{ and } \delta\{k: \xi_k < \alpha - \varepsilon\} = 0.$$

Conversely, if (2) holds for every positive  $\varepsilon$  then  $\alpha = \text{st-lim inf } x$ .

**Remark:** By definition of statistical cluster point [9] we see that theorem 1 and 2 can be interpreted as saying that  $\text{st-lim sup } x$  and  $\text{st-lim inf } x$  are the greatest and least statistical cluster points of  $x$ .

**Theorem 3:** For any sequence  $x$ ,  $\text{st-lim inf } x \leq \text{st-lim sup } x$ .

**Proof:** first let us consider the case when  $\text{st-lim sup } x = -\infty$ . Then  $B_x = \emptyset$ , so for every  $b$  in  $\mathbb{R}$ ,  $\delta\{k: \xi_k > b\} = 0$ . This implies that  $\delta\{k: \xi_k \leq b\} = 1$ , so for every  $a$  in  $\mathbb{R}$ ,  $\delta\{k: \xi_k < a\} \neq 0$ . Hence,  $\text{st-lim inf } x = -\infty$ .

The case in which  $\text{st-lim sup } x = +\infty$  is obvious. Next assume that  $\text{st-lim sup } x$  is finite say  $\beta$  and let  $\text{st-lim inf } x = \alpha$ . For given  $\varepsilon > 0$  we show that  $\beta + \varepsilon \in A_x$ , so that  $\alpha \leq \beta + \varepsilon$ . Since  $\beta = \text{l.u.b. } B_x$  so by theorem 1,  $\delta\{k: \xi_k > \beta + \frac{\varepsilon}{2}\} = 0$ . Hence  $\delta\{k: \xi_k < \beta + \frac{\varepsilon}{2}\} = 1$  and which, in turn implies that  $\delta\{k: \xi_k < \beta + \varepsilon\} = 1$ . Hence,  $\beta + \varepsilon \in A_x$ . But  $\alpha = \inf A_x$  by definition, so we conclude  $\alpha \leq \beta + \varepsilon$ . Since  $\varepsilon$  is arbitrary, we have  $\alpha \leq \beta$ .

This completes the proof.

**Definition:** The real number sequence  $x$  is said to be *statistically bounded* if there is a number  $B$  such that  $\delta\{k: |\xi_k| > B\} = 0$ .

**Remark:** Statistical boundedness implies that  $\text{st-lim sup}$  and  $\text{st-lim inf}$  are finite, so Properties (1) and (2) of Theorems 1 and 2 hold.

**Theorem 4:** The statistically bounded sequence  $x$  is statistically convergent if and only if

$$\text{st-lim inf } x = \text{st-lim sup } x.$$

**Proof:** Let  $\text{st-lim inf } x = \alpha$  and  $\text{st-lim sup } x = \beta$ . First let us assume that  $\text{st-lim } x = \xi$  and  $\varepsilon > 0$  be given. Then  $\delta\{k: |\xi_k - \xi| \geq \varepsilon\} = 0$  and thus  $\delta\{k: \xi_k > \xi + \varepsilon\} = 0$ . This implies that  $\beta \leq \xi$ . Also, we have  $\delta\{k: \xi_k < \xi - \varepsilon\} = 0$  which implies  $\xi \leq \alpha$ . Hence, we have  $\beta \leq \xi \leq \alpha$ . i.e.  $\beta \leq \alpha$ . But by theorem 3,  $\alpha \leq \beta$ . Thus  $\alpha = \beta$ . Conversely, assume  $\alpha = \beta$  and let  $\varepsilon > 0$  be given. Then by theorem 1 and 2 we have  $\delta\{k: \xi_k > \alpha + \frac{\varepsilon}{2}\} = 0$  and  $\delta\{k: \xi_k < \alpha - \frac{\varepsilon}{2}\} = 0$ . But  $\alpha = \beta = \xi$  (say) so we have  $\delta\{k: \xi_k > \xi + \frac{\varepsilon}{2}\} = 0$  and  $\delta\{k: \xi_k < \xi - \frac{\varepsilon}{2}\} = 0$ . Hence  $\text{st-lim } x = \xi$ .

This completes the proof.

### Statistical monotonicity:

In this section we study the concept of statistical monotonicity [13] and some related results.

**Definition:** A sequence  $x = (\xi_n)$  is statistical monotone increasing (decreasing) if there exists a subset  $A \subseteq \mathbb{N}$  with  $\delta(A) = 1$  such that the sequence  $x = (\xi_n)$  is monotone increasing (or decreasing) on  $A$ .

**Definition:** A sequence  $x = (\xi_n)$  is statistical monotone if it is statistical monotone increasing or statistical monotone decreasing.

**Theorem:** If the sequence  $x = (\xi_n)$  is bounded and statistical monotone then it is statistically convergent.

**Theorem:** If  $x = (\xi_n)$  is statistical monotone increasing or statistical monotone decreasing then

$$\lim_{n \rightarrow \infty} \frac{1}{n} |\{k: k \leq n, x_{k+1} < x_k\}| = 0$$

Or

$$\lim_{n \rightarrow \infty} \frac{1}{n} |\{k: k \leq n, x_{k+1} > x_k\}| = 0$$

respectively.

**Remark:** The inverse of these assertions is not correct because of the following example:

Define  $x = (\xi_n)$  by

$$\xi_n = \begin{cases} 1, & \text{if } 2^k \leq n < 2^{k+1} - 1 \text{ for even } k, \\ 0, & \text{otherwise.} \end{cases}$$

Clearly above theorem holds for this sequence but this sequence is not statistical monotone (and not statistically convergent).

**Definition:** (Dense Subsequence) The subsequence  $x' = (\xi_{n_k})$  of  $x = (\xi_n)$  is called a dense subsequence, if  $\square(K_{\infty'}) = 1$ .

**Theorem:** Every dense subsequence of a statistical monotone sequence is statistical monotone.

**Theorem:** The statistical monotone sequence  $x = (\xi_n)$  is statistically convergent if and only if  $x = (\xi_n)$  is statistical bounded.

**Definition:** The sequence  $x = (\xi_n)$  and  $y = (\sigma_n)$  are called statistical equivalent if there is a subset  $M$  of  $\mathbb{N}$  with  $\square(M) = 1$  such that  $\xi_n = \sigma_n$  for each  $n \in M$ . It is denoted by  $x \square y$ .

With this definition we formulate following theorem.

**Theorem:** Let  $x = (\xi_n)$  and  $y = (\sigma_n)$  be statistical equivalent. Then  $x = (\xi_n)$  statistical monotone if and only if  $y = (\sigma_n)$  is statistical monotone.

## References

- [1] R. C. Buck, Generalized asymptotic density, Amer. J. Math. 75(1953), 335-346. MR 14: 854f
- [2] J. S. Connor, The statistical and strong p-Cesàro convergence of sequences, Analysis 8(1988), 47-63. MR 89k: 40013

- [3] J. S. Connor and M. A. Swardson, Strong integral summability and the Stone-Čech compactification of the half-line, *Pacific J. Math.* 157 (1993), 201-224. MR 94f: 40007
- [4] J.S. Connor and M.A. Swardson, Measures and ideals of  $C^*(X)$ , *Annals N.Y. Acad. Sci.* 104(1994), 80-91. MR 95b: 54022
- [5] J.S. Connor and J. Kline, On statistical limit points and the consistency of statistical convergence, *J. Math. Anal. Appl.* 197 (1996), 392-399. MR 96m: 40001
- [6] P. Erdős and G. Tenenbaum, Sur les densités de certaines suites d'entries, *Proc. London Math. Soc.* 59 (1989), 417-438. MR 90h: 11087
- [7] H. Fast, Sur la convergence statistique, *Colloq. Math.* 2(1951), 241-244. MR 14: 29c
- [8] . J.A. Fridy, On statistical convergence, *Analysis* 5(1985), 301-313. MR 87b: 40001
- [9] Statistical limit points, *Proc. Amer. Math. Soc.* 118(1993), 1187-1192. MR94e: 40008
- [10] J. Fridy and C. Orhan, Lacunary statistical summability, *J. Math. Anal. Appl.* 173 (1993), 497-504. MR 95f: 40004
- [11] J.A. Fridy and H.I. Miller, A matrix characterization of statistical convergence, *Analysis* 11(1991), 59-66. MR 92e: 40001
- [12] J.A.Fridy and C.Orhan, statistical limit superior and limit inferior, *Proc. Amer. Math. Soc.* Vol.125, No. 12, 1997, 3625-3631.
- [13] E. Kaya, M. Kucukaslan and R. Wagner, On Statistical Convergence And Statistical Monotonicity, *Annales Univ. Sci. Budapest., Sect. Comp.* 39 (2013) 257-270.
- [14] I.J. Maddox, Steinhaus type theorems for summability matrices, *Proc. Amer. Math. Soc.*45(1974), 209-213. MR 51: 1192
- [15] Some analogues of Knopp's Core Theorem, *Internat. J. Math. & Math. Sci.*, 2(1979), 605, -614. MR 81m: 40012
- [16] Statistical convergence in locally convex spaces, *Math. Cambridge Phil. Soc.* 104(1988), 141-145. MR 89k: 40012

