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# On the Usage in Agricultural Statistics of the New Class of Estimators, Pre-eminent in Sampling Theory

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SUMMARY

This paper gives an exposition of the class of estimators proposed in Srivastava [4], and further investigated in various articles, some of which are included in the References at the end. This class of estimators is pre-eminent in Sampling Theory. It is believed that in almost every situation, it should produce estimators better than those available in the literature. A few directions of research useful in Agricultural Statistics are also indicated. Agricultural Statisticians involved in sampling may do a great service to themselves by developing this class of estimators for their fields of application.

*Key words*: Physical sampling technique, SRSWR, Sample weight function, Linear homogeneous unbiased estimators.

## *1. Introduction*

A series of papers, starting with Srivastava [4], have been published on this method of estimation, which bears the author's name ("Srivastava-Estimation"). Many of the revelant works are listed at the end.

The purpose of this paper is to present some lines of research which may turn out to be particularly useful in Agricultural Statistics.

In what follows, we briefly (but, lucidly) explain the class of estimators and a few major special cases, and discuss some of the main properties of these briefly. Finally, we indicate some new lines of research which may be specially fruitful in Agricultural Statistics.

Let U denote the finite population (or the "Universe") consisting of N units, denoted by $\langle 1, 2 \ldots N \rangle$. For the i-th unit $(i = 1, \ldots, N)$, let $y_i$ denote the value of a variable of interest y. Then, the population total is $(y_1 + \ldots + y_N)$, and will be denoted by Y.

Throughout, let k ($1 \leq k \leq N$) be an integer, and let $\underline{i} = (i_1, \ldots, i_k)$ be an unordered set of k distinct integers chosen out of {1, 2,..., N}. Though $(i_1, \ldots, i_k)$ is unordered, we shall, for convenience, write it as an ordered set with $1 \leq i_1 < i_2 < \ldots < i_k \leq N$.

For any fixed k, let $\psi(\underline{i})$ be a real number defined for all possible $\underline{i}$. (Clearly, the number of choices of $\underline{i}$ is $\binom{N}{k}$. All that we assume about $\psi$ is that it is known function in the sense that for every value of $\underline{i}$, the value of $\psi(\underline{i})$, which is a real number, is known.

Let

$$Q(\psi) = \Sigma_1 \psi(\underline{i}) \tag{2.1}$$

where $\Sigma_1$ denotes a sum which runs over all distinct $\binom{N}{k}$ possible values of $\underline{i}$. In Srivastava [4], the problem of estimation of $Q(\psi)$ was considered (for all k, and for all $\psi$).

Throughout, by a "sample" we shall mean a set of distinct units drawn from the population U. Let $\omega$ denote a sample, and let $|\omega|$ stand for the number of units in $\omega$.

A "Physical Sampling Technique" (PST) will, throughout, signify any method of drawing a sample from the population. In this paper, the theory covers all PST's. Note that a given PST may lead to a sample of variable size. Thus, in Binomial Sampling, a unit $i \in (1, \ldots, N)$ may be selected with probability, say $p_i > 0$. Clearly, in this case, $|\omega|$ will vary between 0 and N. Another example is given by Simple Random Sampling With Replacement (SRSWR). Suppose we draw 5 units using SRSWR. Clearly, $|\omega|$ will now vary between 1 and 5. SRSWR is an example of a PST which may lead to a situation where a particular unit may get drawn more than once. If $\omega'$ is the set of units drawn using such a PST, then in our theory below, we shall consider our sample to be $\omega$ where $\omega$ is the largest set of distinct units contained in $\omega'$.

One may wonder whether we are throwing away information by restricting $\omega'$ to $\omega$. Let $m_i$ ($\geq 0$) be the number of times unit i (= 1, ..., N) occurs in $\omega'$, so that $|\omega'| = \sum_{i=1}^{N} m_i$, and $|\omega|$ equals the number of distinct values of i such that $m_i > 0$. Then, it is intuitively clear that unless the PST is such that the $m_i$ have information concerning $\underline{y}$ $(= (y_1, \ldots, y_N))$, we do not lose any information in restricting $\omega'$ to $\omega$. This fact is also supported by the published literature on this problem. Indeed $\omega$ may give better results. For example, if the PST is SRSWR, then it is known that the arithmetic mean of the y-values of the units in $\omega'$ (say $\bar{y}_{\omega'}$), is a worse estimator of the population mean $\bar{Y} = (Y/N)$ then $\bar{y}_\omega$ when $\bar{y}_\omega$ is the arithmetic mean of the y-value of the units in $\bar{y}_\omega$. (However, it is well known that the Horvitz-Thompson estimator $(\hat{Y}_{HT})$ of Y is not admissible when the sample size is variable, and that a new admissible estimator $(\bar{Y}_{S2})$ (Srivastava [5]) should be used instead. Thus, in particular, under SRSWR, the estimator $\hat{Y}_{S2}$ is the best known estimator (under total ignorance of $\underline{y}$).

Now, consider any arbitrary, but fixed, PST. Let $\omega$ be a sample, and let $p(\omega)$ be the probability of drawing $\omega$ under the given PST. Thus p is the 'sampling measure' induced by the PST.

We now consider the problem of estimation of $Q(\psi)$, given a sample $\omega$ obtained by using a particular PST, with sampling measure p.

Let r be a function which maps samples $\omega$ to real number, i.e., r is a known, finite, real valued function, such that the value of $r(\omega)$ is known for all possible $2^N$ samples $\omega$. If $\omega$ is empty, we take $r(\omega) = 0$. The function r, called a 'sample weight function', was introduced in Srivastava [4], and is a key concept in the development of this class of estimators.

Let t be an integer, with $1 \le t \le N$. Let $\underline{j} \equiv \underline{j}(t) \equiv (j_1, \ldots, j_t)$, with $1 \le j_1 < j_2 < \ldots < j_t \le N$.

Define

$$\pi_r(\underline{j}) \equiv \pi_r(\underline{j}(t)) = \Sigma_2\, p(\omega)\, r(\omega) \tag{2.2}$$

where the sum $\Sigma_2$ runs over all samples $\omega$ which contain the t units $(j_1, \ldots, j_t)$. Now, for a given t (with $1 \le t \le N$), k (with $1 \le k \le N$), and $\underline{i} = (i_1, \ldots, i_k)$ (as before), we define the class $T_r(\underline{i}, t)$. The class $T_r(\underline{i}, t)$ is the set of values of $\underline{j}$ $(= (j_1, \ldots, j_t))$ such that the unordered set $(j_1, \ldots, j_t)$ contains the unordered set $(i_1, \ldots, i_k)$ and furthermore, such that

$\pi_r$ ($\underline{j}$ (t))$\neq$ 0. For all permissible t, and $\underline{i}$ define $v_r(\underline{i}, t)$ to be the number of elements in the set $T_r(\underline{i}, t)$, so that

$$v_r(\underline{i}, t) = |T_r(\underline{i}, t)| \tag{2.3}$$

where, for any set K, |K| denotes the number of elements in K.

Now, for any real number z, let $z^-$ denote the Moore-inverse of z; this means that $z^- = 0$, if $z = 0$, and $z^- = 1/z$ if $z \neq 0$. Also, for all permissible t and $\underline{i}$, we introduce real numbers such that $\alpha(\underline{i}, t) = 0$, if $v_r(\underline{i}, t) = 0$, and such that

$$\sum_{t=1}^{N} \alpha(\underline{i}, t) = 1 \tag{2.4}$$

For any fixed k and $\underline{i}$, and for any given sample ω, define

$$\beta_r(\underline{i}, \omega) = r(\omega) \sum_{t=1}^{N} [\alpha(\underline{i}, t)] [v_r(\underline{i}, t)^- \{ \Sigma_3 [\pi_r(\underline{j}(t))]^- \} \tag{2.5}$$

where, for any given t, the sum $\Sigma_3$ runs over all values of $\underline{j}(t) = (j_1, \ldots, j_t)$, such that the unordered set $\underline{i} (= (i_1, \ldots, i_k))$ is contained in the unordered set $(j_1, \ldots, j_t)$, and furthermore such that the unordered set $(j_1, \ldots, j_t)$ is itself contained in the sample ω. (It is clear that $\Sigma_3$ will run over an empty set if $\underline{i}$ is not contained in ω, and/or if $t > |\omega|$.)

Let

$$\hat{Q}^{Sr}(\psi) \equiv \hat{Q}(\psi) = \Sigma_4 [\beta_r(\underline{i}, \omega)] \psi(\underline{i}) \tag{2.6}$$

where $\Sigma_4$ runs over all values of $\underline{i}$ which are contained in ω. (Note that if $k > |\omega|$, then $\hat{Q}(\psi)$ is undefined.)

In Srivastava [4], the quantity $\hat{Q}(\psi)$ was proposed as an estimator of $Q(\psi)$.

*Remark 2.1*

(1) In Sampling Theory (ST) literature, usually the estimation of Y and $\bar{Y}$, and also of the variance of the proposed estimator of these is considered. The theory related to $\hat{Q}(\psi)$ provides a three-fold generalization of the above. We elaborate these below.

(2) Firstly, we consider $Q(\psi)$ itself. When $k = 1$ and $\psi(\underline{i}) = \psi(i_1) = y_{i1}$, we get $Q(\psi) = Y$, the population total. But, we can choose any value of k, and any function $\psi$. Thus, the first generlization is from Y to $Q(\psi)$. For example, when $k = 2$, and $\psi(\underline{i}) = (y_{i1} - y_{i2})^2$, for all $\underline{i}$, the quantity $Q(\psi)$ is a constant multiple of $S^2$ (the population variance, which equals $(N-1)^{-1}\sum_{i=1}^{N}(y_i - \overline{Y})^2$).

Similarly, if $k = 2$ and $\psi(i_1, i_2) = |y_{i1} - y_{i2}|$, the quantity $Q(\psi)$ is a constant multiple of Gini's mean difference. Also take $k = 2, \psi(i_1, i_2) = (a_{i1} y_{i1} + a_{i2} y_{i2})^2$, where $(a_1, \ldots, a_N) (\equiv \underline{a}$ say) is a fixed set of real numbers. Then, $Q(\psi)$ will be a quadratic form $\underline{y}' \Gamma \underline{y}$, where $\Gamma(n \times n)$ is a matrix of real numbers (which will be polynomials in the a's). Now, quite often, an expression for Var $(\hat{y})$ (where $\hat{y}$ is some estimator of Y, and "Var" stands for "variance") can be written in the form $\underline{y}' \Gamma \underline{y}$, for a suitable choice of $\vec{a}$. For all such situations, the theory discussed here is applicable, and it will provide new classes of estimators, many of which may turn out to be far superior to those available now.

(3) The second dimension of generalization is the function r. Notice that r is unrestricted. It turns out that many of the most famous classes of estimators in ST correspond to simple choices of r. However, other choices may, and often do, give significant improvements. (An example is $\hat{Y}_{S2}$, in the context of SRSWR, mentioned earlier.)

(4) A third dimension of generalization comes through the introduction of the quantities $\alpha(i, t)$, which is a set of n arbitrary real numbers subject to slight restrictions. The idea behind these is as follows. Suppose we wish to estimate a quantity $Q(\psi)$, where $\psi(\underline{i})$ is a function of $\underline{i}$, which is a set of k units from U. Thus, $Q(\psi)$ is a sum of quantities, which are functions of units, taken k at a time. Now, for fixed k, let t be such that $k \le t \le |\omega|$. To estimate $Q(\psi)$, we could look at t units at a time from the sample. This will be illustrated below by working out the two cases where $\alpha(\underline{i}, t)$ equals 1 for $t = 1$ or 2, and equals zeros otherwise.

First, take $t = 1$, and let

$$\alpha(\underline{i}, 1) = 1 \text{ and } \alpha(\underline{i}, t) = 0, \text{ for } t > 1 \tag{2.7}$$

Then,

$$\underline{j}(t) = (j_1) \ (= j, \text{say}),$$

and

$$\psi_r(\underline{j}(t)) \equiv \psi_r(j_1) \equiv \psi_r(j) = \sum_{21} p(\omega)\, r(\omega) \tag{2.8}$$

where $\sum_{21}$ runs over all $\omega$ containing the unit j.

For simplicity and convenience of exposition, henceforth we shall assume that for $t = 1$ and 2, $\psi_r(\underline{j}(t))$ is positive for all permissible values of $\underline{j}(t)$. Thus, $\psi_r(j)$ defined above is always positive. Hence, under (2.7), for $k = 1, \underline{i} = i$, we get

$$\beta_r(i, \omega) = r(\omega)/\psi_r(i) \tag{2.9}$$

For later use, define, for all $i\,(= 1, \ldots, N)$ and for all $\omega$:

$$\begin{aligned} a_{i\omega} &= 1, \text{if } i \in \omega \\ &= 0, \text{otherwise} \end{aligned} \tag{2.10}$$

When $k = 1$, $\underline{i} = i$, $\psi(\underline{i}) = y_i$, we get $Q(\psi) = Y$, and $\hat{Q}^{Sr}(\psi)$ reduces to $\hat{Y}_{Sr1}$, where

$$\hat{Y}_{Sr1} = r(\omega) \sum_{i=1}^{N} \frac{y_i}{\psi_r(i)} \tag{2.11}$$

Now, consider the situation where

$$r(\omega) = 1, \text{ for all possible } \omega \tag{2.12}$$

In this case, $\psi_r(\underline{j})$ reduces to $\psi(\underline{j})$ where

$$\psi(\underline{j}) = \Sigma_2\, p(\omega) \tag{2.13}$$

so that $\psi(\underline{j})$ is the probability that, under the PST being used, the set of t units $(j_1, \ldots, j_t)$ will all be included in the sample. Under (2.12), $\hat{Y}_{Sr1}$ reduces to $\hat{Y}_{HT}$ where

$$\hat{Y}_{HT} = \sum_{i=1}^{N} \frac{y_i\, a_{i\omega}}{\psi_r(i)} \tag{2.14}$$

Now, we consider the case where

$$\alpha(\underline{i}, 2) = 1 \quad \text{and} \quad \alpha(\underline{i}, t) = 0 \text{ for } t \neq 2 \tag{2.15}$$

Under (2.11), $\hat{Q}^{Sr}(\psi)$ reduces (for $Q(\psi) = Y$) to $\hat{Y}_{S12}$

where

$$\hat{Y}_{S12} = \sum_{i=1}^{N} y_i \left[ \sum\nolimits^{*} \frac{1}{\psi(i, i')} \right] \frac{1}{(|\omega| - 1)} \tag{2.16}$$

where

$\sum^{*}$ runs over all units $i'$ ($\neq$ i) in $\omega$.

Notice that $\hat{Y}_{HT}$ utilizes the $\psi_i$, whereas $\hat{Y}_{S12}$ involves the $\psi(i, i')$; thus, in a sense, $\hat{Y}_{S12}$ looks at two units at a time. Notice also that by choosing $\alpha$'s appropriately, we could have a linear combination of $\hat{Y}_{HT}$ and $\hat{Y}_{S12}$. Similarly, there will be an analog (say $\hat{Y}_{Sr2}$) of $\hat{Y}_{S12}$ for the case when (2.11) does not hold just as $\hat{Y}_{Sr1}$ is with respect to $\hat{Y}_{HT}$.

The estimator $\hat{Y}_{Sr2}$, or even $\hat{Y}_{S12}$, have not been studied in any detail, but $\hat{Y}_{Sr1}$ has been investigated in many articles. (So, for example Srivastava and Ouyang [6], [7], and other articles included in the reference.)

## 2. *Discussion of Properties*

We now give a brief and informal discussion of some of the major properties of the class of estimators given by $\hat{Q}^{Sr}(\psi)$. For details, the reader should look into the references.

*Remark 3.1.* In Srivastava [4], it is proven that for all (permissible) k, $\psi$, choices of $\alpha$'s, and functions r, and all PST's, the estimator $\hat{Q}^{Sr}(\psi)$ is unbiased for $Q(\psi)$. Expressions, in reduced form, are provided for $\text{Var}(\hat{Q}^{Sr}(\psi))$, and $\text{Cov}(\hat{Q}^{Sr1}(\psi_1), \hat{Q}^{Sr2}(\psi_2))$ (in an obvious notation). Also, a class of estimators of these quantities, using the samples, is provided.

*Definition.* For any PST, a function r will be called "regular" if it satisfies the condition:

$$\frac{1}{r(\omega)} = \frac{1}{r_{i1}} + \frac{1}{r_{i2}} + \ldots + \frac{1}{r_{in}} \quad (3.1)$$

for *all* non empty samples ω (where $|\omega| = n$, and ω consist of the units $(i_1, \ldots, i_n)$) such that $p(\omega) > 0$, where $r_i$ $(i = 1, \ldots, N)$ are some set of positive real numbers. (Note that (3.1) includes $[(2^N - 1) - g]$ conditions, where g is the number of distinct ω's such that $p(\omega) = 0$. If $g = 0$, then n will take the values (1, 2,..., N), and there will be $\binom{N}{n}$ samples with $|\omega| = n$.)

*Remark 3.2.* (Srivastava and Ouyang [6])

(1) Suppose $\underline{y} > 0$ (i.e., $y_i > 0$ for all i). Also, suppose that (3.1) is satisfied, and also that

$$y_i/Y = \psi_r(i)/r_i \quad \text{for all } i = 1, \ldots, N \quad (3.2)$$

Then,

$$\text{Var}(\hat{Y}_{Sr1}) = 0$$

(2) If r is regular, then $\hat{Y}_{Sr1}$ is admissible in the class of linear homogeneous unbiased estimators of Y.

(3) It is easy to see that when $|\omega|$ is variable, (3.1) can not be satisfied if (2.11) holds. Indeed, when $|\omega|$ is variable, it is well known that $\hat{Y}_{HT}$ is inadmissible. For this situation, the admissible special case of $\hat{Y}_{Sr1}$ is not $\hat{Y}_{HT}$, but $\hat{Y}_{S2}$, where

$$\hat{Y}_{S2} = \sum_{i=1}^{N} a_{i\omega}\, y_i/\pi'_i \quad (3.3)$$

where, for all i,

$$\pi'_i = \sum_{\omega} \frac{p(\omega)\, a_{i\omega}}{|\omega|} \quad (3.4)$$

(4) For fixed sample size case, the theory of $\hat{Y}_{HT}$ has given birth to the so-called "p.p.s. sampling", which says that our PST should be such that the resulting sampling measure p (ω) is such that $\psi_i$ is proportional to $\tilde{y}_i$, where $\tilde{y}_i$ is a guess-value of $y_i$, for all i. Using $\hat{Y}_{S2}$, we now

have "weighted pps sampling", in which we need to have that the $\pi'_i$ are proportional to the $\tilde{y}_i$.

*Remark 3.3.*

(1) In general, suppose that we are given the vector $\underset{\sim}{y}$, and also a measure p using which the sample has been drawn. It is clear that we should like to choose the function r so that equations (3.1) and (3.2) (where, in (3.2), the $y_i$ are replaced by the $\tilde{y}_i$) are satisfied. (The equations (3.1) and (3.2)) taken together are known as Zero-Variance Equations (ZVE), since they lead to zero variance when $\underset{\sim}{y} = \tilde{\underset{\sim}{y}}$.

(2) The ZVE are non-linear. An iterative procedure has been proposed (Srivastava and Ouyang [6], [7]) which converges rapidly. Notice that in the computation of the $\omega_r(i)$, the sum is to be taken over all $\omega$ which contain the unit i. When N is large, the number of such $\omega$'s may become too large. For this, a sampling procedure has been developed which allows the computation of $\psi_r(i)$ relatively easily; this procedure will be described elsewhere.

(3) In Srivastava and Ouyang [6], the "principle of invariance" was offered. This says that Y is invariant under a permutation of the elements of the vector $(y_1, \ldots, y_N)$, or equivalently, under a permutation of the units $(1, 2, \ldots, N)$. This allows us the estimation of Y by estimating the total of a population U* whose y-values are $(y_1^*, \ldots, y_N^*)$ $(= \underset{\sim}{y}^*$, say) where $y_1^* \le y_2^* \le \ldots \le y_N^*$, and where $(y_1^*, \ldots, y_N^*)$ is a permutation of $(y_1, \ldots, y_N)$. Of course, we have to obtain a guess-value $\tilde{\underset{\sim}{y}}^*$ for $\underset{\sim}{y}^*$. Suppose we do have a good guess value $\tilde{\underset{\sim}{y}}^*$.

After drawing the sample $\omega$ (from U), say $\omega = (i_1, \ldots, i_n)$, we look at the vector $(y_{i1}, \ldots, y_{in})$. Suppose $(y'_1, \ldots, y'_n)$ is a permutation of $(y_{i1}, \ldots, y_{in})$ such that $(y'_1 \le y'_2 \le \ldots \le y'_n)$. Let $(j_1, \ldots, j_n)$ be such that $1 \ne j_1 < j_2 < \ldots < j_n \ne N$, and furthermore such that $\tilde{y}_{jh}^*$ is closest to $y'_h$.

Then, we regard our sample to be $\omega^*$ (drawn from U*), where $\omega^*$ consists of the units $(j_1, \ldots, j_n)$. Next, we obtain a guess value $\tilde{\underset{\sim}{y}}^*$ of $\underset{\sim}{y}^*$, and using $\tilde{\underset{\sim}{y}}^*$ in the ZVE, we find the function r by iteration. Having obtained r, we compute the estimate.

*Remark 3.4.* Besides $\hat{Y}_{HT}$, most of the other well known estimators of Y are also special cases of $\hat{Q}^{Sr}(\psi)$. Some of these include the Lahiri-Midzuno, the Hartley-Ross, and the Mickey estimators.

### 3. *Future Lines of Work*

In the papers included in the references, particularly in Srivastava [9], many large areas of research which should be quite fruitful, are pointed out. Here, we discuss three new lines of investigation, which may be very useful in agricultural work.

*Remark 4.1*

(1) This is in continuation of Remark 3.3. Recall $\underset{\sim}{y}^*$ and $\tilde{\underset{\sim}{y}}^*$. If the choice of $\tilde{\underset{\sim}{y}}^*$ is made totally independently of $\omega^*$, then $\hat{Y}_{Sr1}$ (which involves the function r derived from $\tilde{\underset{\sim}{y}}^*$ using the ZVE) will be an unbiased estimate of Y. On the other hand, if $\tilde{\underset{\sim}{y}}^*$ depends in some way upon the $\omega^*$, then some bias may get introduced in $\tilde{Y}_{Sr1}$. However, the biased estimator may still be quite good from the view point of mean square error. Such investigations can be easily carried out using simulation techniques.

(2) A good guess value $\tilde{\underset{\sim}{y}}^*$ may come as a result of having a model-oriented approach. Thus, the set $(y_1^*, \ldots, y_N^*)$ can be considered to be a set of order statistics from some population whose form we might be able to determine from previous experience. Indeed, it should be useful to study the dependence of $(r_1, \ldots, r_N)$ upon $(y_1^*, \ldots, y_N^*)$ such that the ZVE are satisfied, assuming that $|\omega|$ is fixed, and $p(\omega)$ is a constant (i.e., SRSWOR). For different important super-populations, one could obtain the order statistics, consider the same to be $\tilde{\underset{\sim}{y}}^*$, and then obtain r, and study the behavior of $\hat{Y}_{Sr1}$ through simulation. Sometimes, in the above process, one may use $\omega^*$ to get some clues to $\tilde{\underset{\sim}{y}}^*$. Of course, this will make $\tilde{Y}_{Sr1}$ biased and nonlinear, but the final result may turn out to be excellent. Indeed, in some examples tried by the author, this is the case.

(3) Another line of investigation consists of applications to "Successive Sampling" situation. In this case, $\tilde{\underset{\sim}{y}}$ may be the value of $\underset{\sim}{y}$ estimated, say, in the previous year. Agricultural forecasts are made every year.

Thus, it should be quite worth while to investigate this direction of research, which may give a much improved estimate of Y.

(4) Finally, there is the area of "Subsampling", which arises in almost every sampling activity in practice. Suppose there are N primary units, the j-th primary unit having $M_j$ secondary units. We choose a few (say n) primary units, and in each chosen primary unit, we select a few secondary units. Suppose, SRSWOR is used at both stages.

For each selected primary unit, we can estimate the total of the subunits by using the previous methods. Next, a function r can be worked out by using the vector $(M_1, \ldots, M_N)$ i.e., by considering it to be roughly proportional to $(Y_1, \ldots, Y_N)$ where $Y_i$ is the total for the i-th primary unit.

(5) The above illustrates a few lines for research which should be fruitful. Of course, these can be combined with many other suggestions given in other papers, including Srivastava [9].

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