

COMPUTER METHODS
FOR GENERATING PSEUDO-RANDOM NUMBERS
FROM PEARSON DISTRIBUTIONS AND
MIXTURES OF PEARSON AND UNIFORM DISTRIBUTIONS

by

Donald Gale Thomas

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APPROVED:

Chairman, Richard G. Krutchkoff, PhD.

Boyd Harshbarger, PhD.

Whitney L. Johnson

Raymond H. Myers, PhD.

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I. INTRODUCTION

The advent of the modern high speed computer has brought many changes in our society. Complex problems, in almost every discipline, heretofore unsolvable in a lifetime because of the massive computations involved, may now be solved in minutes with the aid of these high speed computers.

One technique, made particularly attractive by the computer era is that of Monte Carlo methods which comprise that branch of mathematics concerned with synthetic experiments involving random numbers. These methods are often useful on a wide variety of problems beyond the available resources of theoretical mathematics.

Since large sequences of random numbers are desired, techniques have been devised for generating them in a completely deterministic manner such that the resulting sequence of numbers, often called pseudo-random numbers, appears random.

In this thesis, a brief survey of existing methods for generation and testing of pseudo-random numbers is presented. One serious limitation inherent in these generation methods is that they are not easily modified to produce random numbers from distributions other than those for which they were written.

To overcome this limitation Cooper, Davis and Dono (1965) developed a computer program in FORTRAN II which generates random numbers from Pearson distributions. The distribution may be specified by supplying the program with either the first four moments of the desired distribution or sample data from that distribution. The program then

computes and prints out the parameters for the Pearson distribution fitted and if desired, generates random numbers from said distribution and/or produces a graph of the distribution.

The program has been considerably revised and improved as well as converted to be used as a FORTRAN IV subroutine. This subroutine is entered from the mainline program by using the FORTRAN call statement

CALL PURGE2(N1,N2)

where N1 and N2 are arguments which describe the option desired.

Initially, depending on the option selected, the subroutine reads data cards (provision is also made for internal specification of moments) which describe the Pearson distribution to be fitted. The distribution is fitted and parameters for the Pearson curve with origin at the mean are printed. At this point, one hundred random numbers are generated (if the generation option was selected) and returned to the calling program as implied arguments via the COMMON statement. If desired, sample moments from the generated data are calculated.

If more random numbers are desired from the same distribution, the subroutine may be recalled, for each batch of one hundred numbers required, by an argument option which does not necessitate refitting the curve. This procedure produces ten to twenty thousand random numbers per minute.

A graph of the distribution may be obtained on the final call (the graph option destroys the facility for further generation without refitting). The first four moments of the Pearson distribution along with β_1 , β_2 and K may be printed as well as comparable values

calculated from the generated numbers.

In order to remove the restriction of generating pseudo-random numbers from only unimodal distributions as done in the original version of PURGE, another subroutine is developed which allows random numbers to be generated from a mixture of distributions. Any proportion of two Pearson distributions, a normal distribution with arbitrary mean and variance and a uniform distribution on any finite interval may be used in the mixture. The theoretical moments for the mixture are calculated and, if desired, sample moments calculated from the generated random numbers.

When Pearson distributions are to be included in the mixture, this subroutine uses as input binary card output from the PURGE2 subroutine consisting of the cumulative distribution function of the Pearson distribution(s) along with necessary parameters for the generation of pseudo-random numbers from the distribution(s). With this data, pseudo-random numbers may be generated from Pearson distribution(s) by the same technique used in PURGE2.

The subroutine is entered by the FORTRAN statement

```
CALL MIX(N1,N2)
```

where N1 and N2 are arguments, similar to those of PURGE2, which describe the option desired. Initially the subroutine reads a data card specifying the proportion of distributions to be mixed then the Pearson data decks if necessary. For each pseudo-random number generated, a uniform random number is generated which determines the distribution from which to generate the pseudo-random number. As in PURGE2, batches

of one hundred random numbers are generated per call.

If desired, a graph of the distribution may be obtained on the final call. Unlike PURGE2 which obtains its graph from the distribution function, the MIX subroutine obtains its graph from ten thousand random numbers generated from the mixture. All other aspects of the MIX subroutine are similar to PURGE2.

Provision is made in both subroutines for regenerating the same sequence of numbers in the same or different computer runs as well as avoiding regeneration in different computer runs.

A small Monte Carlo investigation of the robustness of three methods of confidence interval estimation to departures from normality is given as an application of the aforementioned computer programs.

Flowcharts along with FORTRAN listings of both subroutines are given in the Appendix.

II. A BRIEF SURVEY OF METHODS OF GENERATING PSEUDO-RANDOM NUMBERS

2.1 Definition and Use of Pseudo-Random Numbers

With the advent of high speed computers, a number of techniques in physics, operations research, applied mathematics, statistics and many other disciplines now involve what are called Monte Carlo calculations. Such calculations sometimes require large sequences of random numbers from various probability distributions.

An early approach to the problem of obtaining sufficient random numbers to handle problems involving Monte Carlo methods was to generate them by some mechanical means such as the electronic roulette wheel described by Brown (1951), record them in machine readable form and read them into the computer as needed. Since almost all computers are input-output limited, this method is entirely too slow.

One of the first papers on improved techniques for generating random numbers was presented at Harvard in September, 1949, by Lehmer (1951). He defined a pseudo-random sequence to be "a vague notion embodying the idea of a sequence in which each term is unpredictable to the uninitiated and whose digits pass a certain number of tests, traditional with statisticians and depending somewhat on the uses to which the sequence is to be put." Here "uninitiated" refers to a person without a priori knowledge of how the numbers are obtained.

2.2 Common Methods of Generating Pseudo-Random Numbers

A number of methods have been proposed for the generation of pseudo-random numbers hereafter referred to simply as random numbers.

Generally these methods follow the following pattern.

A starting number is selected from which the first random number is determined. Once started, the $N+1$ th number is determined from the N th number. It follows then that if the same starting number is used for two sequences of random numbers, generated by the same method, the sequences are identical. The starting number of many random number generators is the same for different computer runs and care should be taken in subsequent runs to insure that the same batch of pseudo-random numbers is not used repeatedly thus invalidating the experimental results obtained.

This property of "repeatability" is extremely desirable when testing or debugging a computer program in which even the order of executing the instructions may depend upon the value of a generated random number. This characteristic is also useful if it is desired to make conditional use of a sequence of random numbers depending, for example, on whether the mean or variance lies within acceptable limits. These statistics may be calculated, for a large sequence, without storing any of the numbers in the sequence. The sequence can then be regenerated for further calculations, if desired, without requiring a large amount of computer storage to contain the generated numbers.

Another characteristic of all pseudo-random number generators is that the sequence repeats itself. The total number, N , of numbers generated is usually referred to as the period. Fortunately, in most cases the period has been determined mathematically for the generators

commonly used and can be made quite large by careful selection of parameters used in generation.

2.21 Mid-square Methods

Metropolis (1956) gives an interesting account of the mid-square method of random number generation. This was one of the first methods of generating random numbers, adapted for use on high speed computers, but has generally been discarded since it does not have a very long period. The period must be found by trial for each starting number and the sequence generally does not return to the starting data to repeat, i.e. after the first $n + m$ numbers have been generated, the sequence may repeat beginning with the m th number.

It can be described as follows. Beginning with an n (usually even) digit number, say x_0 , the first random number x_1 is obtained by calculating x_0^2 and extracting the middle n digits from it. x_2 is obtained from the middle n digits of x_1^2 , etc.

The largest period given by any of the starting numbers used in the Metropolis paper is about 10^6 with the average being about 10^4 .

2.22 Multiplicative Congruential Methods

Another class of generation methods is called multiplicative congruential or power residue methods. They can be defined by the congruence relation

$$(2.1) \quad x_{n+1} \equiv ax_n \pmod{m}$$

introduced by Lehmer (1951). To begin the sequence $\{x_n\}$ of non-negative integers, a positive integer x_0 is chosen as the starting value. This

number is multiplied by another integer a called the multiplier whereupon the product is divided by an integer m , called the modulus, which is positive and greater in magnitude than the other two. The resulting remainder is x_1 , the first pseudo-random number generated. The next pseudo-random number is obtained by replacing x_0 with x_1 and repeating the same calculations. In order to obtain numbers in the interval $[0,1)$, the sequence $\{x_i/m\}$ is formed.

Clearly, this sequence must eventually repeat itself since it can contain at most m different numbers with each number in the given sequence determined by its predecessor. Methods for insuring that the sequence will have maximum period m are given in an IBM (1959) report on this method. This report gives the mathematical development and includes an appendix providing programming illustrations for binary and decimal computers.

Because of its speed and excellent statistical properties which may be obtained by proper choice of x_0 , a and m , this method of generating uniform random numbers is the one most widely used at this time.

2.23 Mixed Congruential Methods

The mixed congruential methods are very similar to the multiplicative methods which are a special case of them and are defined by the congruence relation

$$(2.2) \quad x_{n+1} \equiv ax_n + c \pmod{m}$$

introduced by Coveyou (1960) and Rotenberg (1960).

In this case c is an integer which is added to the product ax_n before division by m . Otherwise the computations are the same as for the multiplicative case. Hull and Dobell (1962) give conditions on x_0 , a , c and m which insure maximum period m .

2.24 Multiplicative vs. Mixed Generators

The underlying theory for mixed congruential generators is simpler than that of multiplicative methods and the periods are longer although both can be extremely long. The only disadvantage of the mixed methods seems to be their statistical properties. Although in general their statistical behavior is quite good, in some respects it is completely unacceptable in a small proportion of cases. Hull and Dobell (1962) report tests of 600 different multipliers about one percent of which they believe to be unacceptable in the sense that they lead to ridiculously large values of X^2 , some as large as 900. They also report tests made with 513 different multipliers using the multiplicative congruential method and "the results were entirely consistent with the hypothesis that the sequence was drawn at random from the uniform distribution".

MacLaren and Marsaglia (1965) report the results of extensive testing of both methods of generating random numbers including two new methods:

The first new method uses a table of random numbers from which a random number U is obtained. Once the original table is exhausted, new numbers are produced by a transformation of the form

$$(2.3) \quad U' = aU + c \pmod{2^{27}}$$

where a and c are chosen such that the transformation is one-to-one and onto, hence the transformed table will be random if the original table was.

The second new method involves two different generators

$$(2.4) \quad U_{k+1} = (2^{17} + 3)U_k \pmod{2^{35}}$$

$$(2.5) \quad V_{k+1} = (2^7 + 1)V_k + 1 \pmod{2^{35}}$$

with one used to shuffle the sequence produced by the other. Initially, $U_0 = 1$ and $V_0 = 0$. A table of 128 locations in core is filled with the numbers U_1, \dots, U_{128} . To generate X_k , the k th random number to be used, the first 7 bits of V_k is used as an index to get X_k from the table. The location of X_k in the table is refilled with the next number from the generator (2.4).

Both new methods passed the tests whereas the conventional multiplicative and mixed congruential methods did not. The tests used here were somewhat more stringent than those usually applied although not at all unreasonable.

2.25 Other Methods

Most of the effort, to date, has been in the area of generating continuous uniformly distributed random variables. The uniform distribution is equated such a high level of importance because any continuous distribution can be transformed into the uniform distribution implying that the uniform distribution may be transformed into any continuous distribution, viz. the reverse of the transformation that

transforms the desired distribution into the uniform. See for example Kendall and Stuart (1963).

Marsaglia (1961) gives methods for expressing a random variable in terms of a uniform random variable and also a method for generating exponential random variables. A summary of methods for generating normal random variables is given by Muller (1959). A discussion of various methods for generating random variables is given in the Handbook of Mathematical Functions published by the United States Department of Commerce (1964). Additional references may be found in a comprehensive bibliography given in Hull and Dobell (1962).

III. A BRIEF SURVEY OF METHODS OF TESTING RANDOM NUMBERS

3.1 Necessity for Testing

A note of warning should be taken from Lehmer's definition of pseudo-random numbers. One should not proceed blindly using random numbers for a problem without first making sure that they satisfy the requirements of the particular problem at hand.

If the outcome of a Monte Carlo simulation is critically dependent on, say whether or not the random numbers used have a high serial correlation, it would behoove the user to test them for such, or at least use a method of generation in which the order or magnitude of the serial correlation is known to be small. More than one Monte Carlo simulation has given erroneous results simply because the user failed to check certain properties of the pseudo-random number generator used, which turned out to be critical in his problem. See Hull and Dobell (1962) and Coveyou (1960) for example.

MacLaren and Marsaglia (1965) report that "random numbers generated by mixed congruential methods gave poor results in a number of Monte Carlo calculations, notably those involving order statistics. . . . The principal difficulty seems to be that certain simple functions of n-tuples of uniform random numbers do not have the distribution that probability theory predicts." They discuss the performance of two new generators which seem to overcome the difficulties inherent in the other methods.

Hull and Dobell (1962) mention a private communication with

R. R. Coveyou in which he "refers to experiences in which special correlation within a sequence has caused erroneous results in Monte Carlo calculations, in spite of the fact that routine statistical tests did not reveal the existence of such correlation" and "draws attention to the need for more quantitative information about the reliability of tests."

To illustrate the point that tests should be made to insure that the random numbers satisfy the requirements of the problem at hand, consider the case of numerical integration. Here, the order of the generated numbers is not important. It is not hard however, to think of cases where the order of the generated numbers would be extremely important. For example, suppose we have a population of 10,000 items and we wish to select a simple random sample of 100 items from this population in order to observe some characteristic of the sample and make inferences about the population. If we assume the population is numerable, we may set up a random number generator which generates uniform random numbers on the interval $[1,10000]$ and take the first 100 numbers generated as the item numbers for our sample. If the order of the first 100 pseudo-random numbers generated is not sufficiently random and the population is not homogeneous, our sample results will be seriously biased.

A simple technique for testing random number generators would be to try them on a similar problem for which the answer is known. See Chapter VII for an example using the $N(0,1)$ distribution, i.e. a normal distribution with mean zero and variance one.

3.2 Tests of Fit

Often it is desired to test a set of numbers to determine if they could have come from a particular distribution. This is a standard question for statistical techniques and many tests have been devised and studied.

3.21 χ^2 Goodness of Fit

Suppose the data is divided into k classes with X_1, X_2, \dots, X_k observations in each class. Let us define the expected values in the corresponding classes a priori to be m_1, m_2, \dots, m_k such that $\sum_{i=1}^k X_i = \sum_{i=1}^k m_i = n$. Thus $p_i = m_i/n$ is the probability of an observation falling in the i th class. We wish to test the hypothesis that the sample distribution came from a population with the given set of m_i .

An approximate test of this hypothesis is given by obtaining the probability of getting a χ^2 with $(k-1)$ degrees of freedom greater than the computed

$$\chi_0^2 = \sum_{i=1}^k \frac{(x_i - m_i)^2}{m_i} .$$

We reject the hypothesis if this probability is unusually small, say 0.05 or less. Such a test is known as the χ^2 goodness of fit test and its theoretical aspects are discussed by Kendall and Stuart (1961). Examples of its use in testing random numbers are given in Taussky and Todd (1956), Hull and Dobell (1962 and 1964), and MacLaren and Marsaglia (1965). Particular attention should be given to the power of the test which may be calculated with the aid of exact tables, for $\alpha = 0.05$,

given by Patnaik (1949).

3.22 Kolmogorov Statistic

An alternative to the χ^2 goodness of fit test is given by the Kolmogorov statistic which is based on deviations of the sample distribution function $S_n(x)$ from the completely specified hypothetical distribution function $F_0(x)$. The measure of deviation is the maximum absolute difference between $S_n(x)$ and $F_0(x)$ given by

$$D_n = \sup_x |S_n(x) - F_0(x)|.$$

The asymptotic distribution of D_n was obtained by Kolmogorov in 1933 and is completely distribution-free under $H_0: F(x) = F_0(x)$.

The advantage of this method over all other methods is that D_n may be used to set confidence limits for a continuous distribution function as a whole. See Kendall and Stuart (1961) for theory and examples.

3.23 Moments

Another procedure that is easily applied is to calculate the moments of the random sequence and compare them visually with their theoretical values. Usually only the first four moments are used due to the large sampling variability of higher moments. As the sample size increases, the sample moments should converge to their true values which are, if all is well, the theoretical values under consideration.

3.3 Tests of Performance

The aforementioned tests of fit do not give any indication of

the order in which the random numbers are drawn. Once it is known that the proper distribution is being generated, tests on the order of the random variables should be made, if the order is important for the particular problem being investigated.

3.31 Runs Up and Down

An example of one such test of order is given by Taussky and Todd (1956). The number of runs of length 1 through 4 and ≥ 5 were determined from 16 sets of 1024 numbers using a multiplicative congruential generator. The observed average number of runs was then compared visually with the expected average as well as the observed variance with the expected variance and the results were considered satisfactory. A disadvantage of this method is that these expected values may be somewhat difficult to calculate for non-uniform distributions.

3.32 Runs Above and Below Mean

Taussky and Todd (1956) also include tests of runs above and below the mean based on 16 sets of 1024 numbers from the uniform distribution giving tabulated values for run lengths from 1 to 10, comparing visually the observed average number of runs with the expected number. Here again the same difficulties may be encountered for non-uniform distributions.

3.33 Serial Correlation

Serial correlation in a sequence of random numbers refers to the

correlation between a random number and its i th successor. Coveyou (1960) gives a method for estimating the serial correlation and determining the parameters in mixed congruential methods such that it will be small.

3.34 Other Tests of Performance

Hunter (1960) gives a test for repeating cycles. Additional tests which are more stringent than those usually applied, although not at all unreasonable, are given by MacLaren and Marsaglia (1965). They include tests on pairs, triples, maximum and minimum of a set of n uniform variates and the sum of n uniform variates.

An extensive discussion of testing random numbers including examples and computer programs for performing the tests is given in an IBM Technical Report by Gorenstein (1966).

IV. PEARSON'S SYSTEM OF FREQUENCY CURVES

All of the previously mentioned methods for generating random numbers have a serious limitation in that they are designed to generate a specific distribution and are generally not easily modified to generate other distributions. Obviously, a method for generating random variables from a wide variety of continuous distributions would be highly desirable.

In order to accomplish this, a new approach was devised by Cooper, Davis and Dono (1963) who wrote a versatile computer program, PURGE, to generate random numbers from the Pearson system of frequency curves.

4.1 Definition and Theory

The family of unimodal frequency functions obtained as solutions to the differential equation

$$(4.1) \quad \frac{dy}{dx} = \frac{y(x - a)}{b_0 + b_1x + b_2x^2}$$

are known as Pearson distributions. The form of the solution depends on the values of the constants a , b_0 , b_1 and b_2 , which may be shown to be related to the moments of the curve. A characteristic of curves of the family (4.1) is that they are completely determined by their first four moments, μ_1' , μ_2 , μ_3 and μ_4 .

In equation (4.1), it is evident that the mode is at the point $x = a$. If we translate the origin to the mode, this equation may be written in the form

$$\frac{d}{dx}(\log y) = \frac{x - a}{B_0 + B_1(x - a) + B_2(x - a)^2}$$

or

$$(4.2) \quad \frac{d}{dx}(\log y) = \frac{X}{B_0 + B_1X + B_2X^2} .$$

We may now obtain two main Pearson types depending on whether the denominator on the right has real or imaginary roots.

4.2 Types

Type I (Real roots)

We may write

$$B_0 + B_1X + B_2X^2 = B_2(X + a_1)(X - a_2) \quad a_1, a_2 > 0$$

then

$$\begin{aligned} \frac{d}{dx}(\log y) &= \frac{X}{B_2(X + a_1)(X - a_2)} \\ &= \frac{a_1}{B_2(a_1 + a_2)} \cdot \frac{1}{(X + a_1)} + \frac{a_2}{B_2(a_1 + a_2)} \cdot \frac{1}{(X - a_2)} \end{aligned}$$

whereupon

$$y = Y_0(X + a_1)^{\frac{a_1}{B_2(a_1 + a_2)}}(X - a_2)^{\frac{a_2}{B_2(a_1 + a_2)}}$$

which may be written in the form

$$y = Y_0 \left\{ 1 + \frac{x}{a_1} \right\}^{M_1} \left\{ 1 - \frac{x}{a_2} \right\}^{M_2}$$

where

$$\frac{M_1}{a_1} = \frac{M_2}{a_2} .$$

If the origin is at the mean

$$(4.3) \quad y = Y_0 \left(1 + \frac{x}{A_1}\right)^{M_1} \left(1 - \frac{x}{A_2}\right)^{M_2}$$

where

$$A_1 + A_2 = a_1 + a_2$$

and

$$\frac{M_1 + 1}{A_1} = \frac{M_2 + 1}{A_2} \cdot$$

The constants Y_0 , M_1 and M_2 are determined by integrating the curve over its range from $-a_1$ to a_2 , (see Elderton 1953). This curve varies in shape from bell to U, and, twisted J.

Type IV (Imaginary roots):

In this case we may write

$$\frac{d(\log y)}{dx} = \frac{x}{B_2 \left[\left(\frac{x + B_1}{2B_2} \right)^2 + \left(\frac{B_0 - B_1}{B_2 - 4B_2^2} \right)^2 \right]}$$

or

$$= \frac{x}{B_2 [(x - g)^2 + d^2]}$$

thus

$$\log y = \log Y_0 + \frac{1}{2B_2} \log [(x + g)^2 + d^2] - \frac{g}{B_2 d} \tan^{-1} \frac{x + g}{d}$$

$$y = Y_0 [(x + g)^2 + d^2]^{\frac{1}{2} B_2} \exp \left[\frac{-g}{B_2 d} \tan^{-1} \frac{x + g}{d} \right]$$

usually written

$$y = Y_0 \left(1 + \frac{x}{A^2}\right)^{-M} \exp(-V \tan^{-1} x/A)$$

where the origin is $VA/(2M - 2)$ after the mean.

The curve may also be written as

$$y = Y_0 \left[1 + \left(\frac{x}{A} - \frac{V}{R} \right)^2 \right]^{-M} \exp \left[-V \tan^{-1} \left(\frac{x}{A} - \frac{V}{R} \right) \right]$$

where

$$R = 2M - 2, \text{ with origin at the mean.}$$

The curve is of unlimited range in both directions and is bell shaped. For determination of the constants as well as the derivation of other Pearson curves see Elderton (1953).

Pearson gives a criterion to distinguish the main types of Pearson curves. He defines

$$K = \frac{\beta_1 (\beta_2 + 3)^2}{4(2\beta_2 - 3\beta_1 - 6)(4\beta_2 - 3\beta_1)}$$

with $\beta_1 = \mu_3^2 / \mu_2^3$ and $\beta_2 = \mu_4 / \mu_2^2$ being coefficients of kurtosis and skewness respectively. For Type I curves, K is < 0 and for Type IV curves $0 < K < 1$. Table 1 gives equations of the Pearson curves with origin at the mean along with criterion for K and certain remarks about the curves.

Pearson and Hartley (1962) give a diagram (Table 2) plotting β_1, β_2 to rectangular axes, from which, one may determine the appropriate type of Pearson curve for given β_1 and β_2 . This chart covers Types I-VII.

4.3 Uses

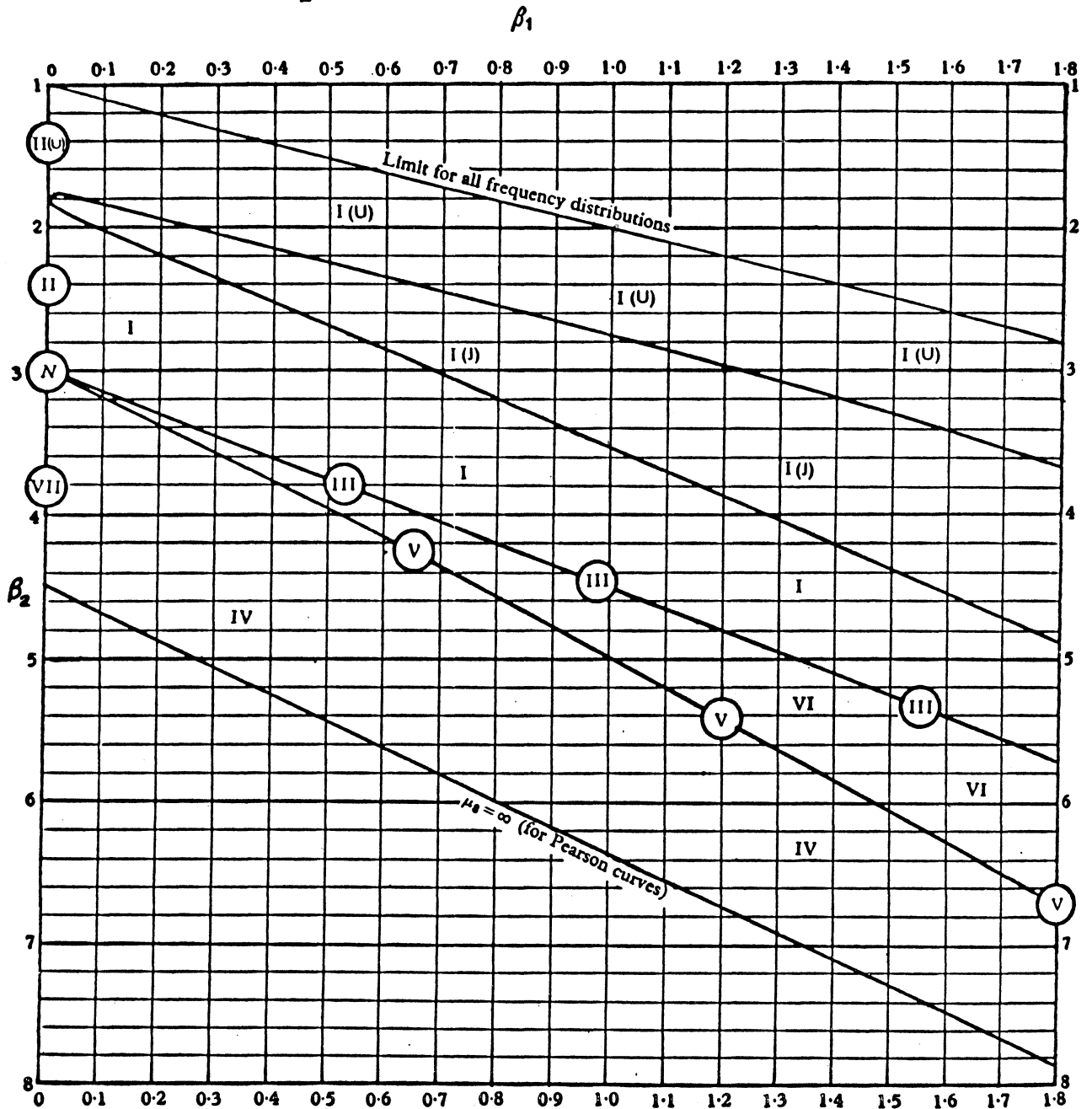
Pearson curves were originally used in actuarial statistics by calculating moments from a large number of observations and fitting

Table 1. Types of Pearson Curves Used*

Pearson Main Types	Equation with origin at the mean	Criterion	Remarks
I	$Y = Y_e (1+X/A_1)^{M_1} (1-X/A_2)^{M_2}$	κ negative	Limited range; skew; usually bell-shaped, but may be U-shaped, J-shaped or L-shaped.
IV	$Y = Y_0 [1+(X/A-V/R)^2]^{-M} e^{-V \tan^{-1}(X/A-V/R)}$	$0 < \kappa < 1$	Unlimited range; skew; bell-shaped.
VI	$Y = Y_e (1+X/A_1)^{-Q_1} (1+X/A_2)^{Q_2}$	$\kappa > 1$	Unlimited range in one direction; skew; bell-shaped, but may be J-shaped.
Subtypes			
Normal	$Y = Y_0 e^{-X^2/C}$	$\kappa=0, \beta_1=0, \beta_2=3$	Unlimited range; symmetrical; bell-shaped.
II	$Y = Y_0 (1-X^2/A^2)^M$	$\kappa=0, \beta_1=0, \beta_2 < 3$	Approximated by Type I. Limited range; usually bell-shaped, but U-shaped when $\beta_2 < 1.8$; symmetrical.
VII	$Y = Y_0 (1+X^2/A^2)^{-M}$	$\kappa=0, \beta_1=0, \beta_2 > 3$	Type IV with $V=0$. Unlimited range; symmetrical; bell-shaped.
III	$Y = Y_e (1+X/A)^P e^{-GX}$	$2\beta_2=6+3\beta_1$	Unlimited range in one direction; usually bell-shaped, but may be J-shaped.
V	$Y = Y_e (1+X/A)^{-P} e^{(P-2)/(1+X/A)}$	$\kappa=1$	Approximated by Type VI. Unlimited range in one direction; bell-shaped.
VIII	$Y = Y_e (1+X/A)^{-M}$	$\kappa < 0, \lambda=0, 5\beta_2-6\beta_1-9 < 0$	Type I with $M_2=0$.
IX	$Y = Y_e (1+X/A)^M$	$\kappa < 0; \lambda=0; 5\beta_2-6\beta_1-9 > 0, 2\beta_2-3\beta_1-6 < 0$	Type I with $M_2=0$.
X	$Y = Y_e e^{-GX}$	$\beta_1=4, \beta_2=9$	Type III with $P=0$. Exponential form from finite ordinate at $-G^{-1}$ to infinitesimal ordinate at ∞ ; J-shaped.
XI	$Y = Y_e (1+X/A)^{-M}$	$\kappa > 1, \lambda=0, 2\beta_2-3\beta_1-6 > 0$	Type I with $M_2=0$. J-shaped.
XII	$Y = Y_e (1+X/A_1)^{M_1} (1-X/A_2)^{M_2}$	$5\beta_2-6\beta_1-9=0$	Special case of Type I, twisted J-shape.

*This table is a modified version of Table VI. given by Elderton (1953). His book should be consulted for calculation of constants.

Table 2.* Chart relating the type of Pearson frequency curve to the values of β_1 , β_2 .



*Reproduced from Pearson and Hartley (1962), Table 43, p. 210.

a Pearson curve which would satisfactorily represent the observations in order to allow accurate graduation and interpolation. For this purpose they are quite satisfactory.

The method has been criticized when the observed data are samples from a population and it is desired to find a mathematical equation satisfactorily representing that population. "In such cases the moments calculated from observation are only estimates of population-moments and they do not, in general, lead to the most efficient estimates of the population parameters", Kendall and Stuart (1963).

"In many instances experience has shown the value of the Pearson curves in approximating, on the basis of known moments, to the distributions of frequency functions which are either undetermined or are not readily expressed in simple form. In addition, these curves, of course, represent exactly the distributions of a number of statistics in common use, e.g. χ^2 , t and F", Pearson and Hartley (1962).

V. PURGE2 SUBROUTINE

The advent of modern high speed computers makes possible another use of Pearson curves . . . that of a highly versatile method of generating random numbers for a whole family of unimodal distributions, by simply supplying the first four moments of the distribution.

5.1 Description and Purpose

As a means to this end, three members of the IBM Scientific Computation Department, Cooper, Davis and Dono, wrote a computer program, "Pearson Universal Random Distribution Generator" (PURGE) to do just that. This program was originally written for the IEM 7090 system in FORTRAN II and has been considerably revised and improved, by this author, to be used as a subroutine (PURGE2) on the IBM 7040-1401 system in FORTRAN IV.

The subroutine is entered by use of the FORTRAN call statement

```
CALL PURGE2(N1,N2)
```

where N1 and N2 are arguments which specify the option desired, see Table 3. Initially, depending on the option selected, the subroutine reads data cards which describe the Pearson distribution to be fitted. The distribution may be described either by its first four moments (provision is also made for internal specification of moments) or by sample data from the distribution which may be specified in various formats and fitted with several options. The distribution is fitted and parameters for the Pearson curve with origin at the mean are printed.

At this point, up to one hundred random numbers are generated (if the generation option was selected) and returned to the calling program as implied arguments by placing the FORTRAN instruction

COMMON/Z2/RDS(100)

in the calling program. After each call to PURGE2, the new batch of random numbers will be stored in the array RDS and may be referenced in that array. If desired, moments from the generated data are calculated.

If more random numbers are needed from the same distribution, the subroutine may be recalled, for each batch of one hundred numbers required, by an argument option which does not necessitate refitting the curve. This procedure produces about ten thousand random numbers per minute.

Available output options will print the moments used to determine the curve type as well as β_1 , β_2 and K along with sample values of these statistics calculated from the generated random variables. After the last batch of random variables has been generated, a graph of the distribution function may be obtained. One should not graph the distribution then attempt to generate additional random numbers from it, since the graph routine shares part of its storage with the cumulative distribution function and thus destroys the facility for further generation without refitting the distribution.

Additional speed in generation may be obtained by electing an option which does not calculate the moments of the generated numbers. The speed of generation is doubled when this option is used, producing

about twenty thousand random numbers per minute on the IBM 7040.

A special option is also available which allows moments for a new distribution to be supplied by the calling program without being read in on cards. This option may be particularly useful when dealing with empirical Bayesian statistics.

5.2 Method of Operation

If moments are given, the program calculates β_1 , β_2 and K from which it determines the appropriate Pearson type. If raw point data are given, the program determines the appropriate Pearson type using moments calculated from the data.

Once the Pearson type has been determined, the parameters for the curve with origin at the mean are calculated and printed along with the type of curve fitted. Pearson Types I, IV, III and the normal curve may be fitted as well as subtypes of them. An additional option allows all but Type III to be "force fitted" to a given set of moments or data, i.e. the usual Pearson criterion for determining types is overridden and parameters are calculated for the specific Type from the given data. This procedure, intended for use with similar distributions, will not always yield a valid distribution. For example, if a U-shaped distribution is forced into a normal distribution, FORTRAN errors such as attempting to take the square root of a negative number are encountered. Error messages are automatically printed under these conditions and the program continues although the results are incorrect.

If it is desired to generate random numbers from the fitted distribution, the distribution function is numerically integrated by Simpson's Rule as given in Scarborough (1958). The interval of integration is divided into 5120 equal parts (except 512 for the normal*) which divides the area under the curve into 2560 pieces. The number 2560 was chosen because it is large enough to give good results and yet not so large that it requires too much machine storage. The area of each piece is then accumulated in 2560 cells to obtain the cumulative distribution function (c.d.f.) which takes on values from 0 to 1. The computer time, on the IBM 7040-1401 system, required for all operations up to this point is about two-thirds of a minute.

For the actual random number generation, a mixed congruential uniform random number generator is used to randomly select points on the c.d.f. from which the random numbers with the required distribution are determined. This generator is a library function at the Virginia Polytechnic Institute Computing Center and is not coded in the program. It was developed and tested by Kaercher (1962), using the method of Rotenberg (1960) and employs the congruence relation

$$x_{n+1} \equiv (2^7 + 1)x_n + 311715164025_{(8)} \pmod{2^{35}}$$

with $x_0 = 0$. The subscript on the constant denotes it to be in octal notation. The constant $311715164025_{(8)}$ was chosen since it is odd and approximately equal to $[(.5 + \sqrt{3}/6)2^{35}]$ which was shown by Coveyou (1960) to cause the least serial correlation.

* It is not recommended that this program be used to generate normal random numbers since methods are available which are several times faster.

Kaercher reports satisfactory statistical results were obtained from χ^2 tests, tests on the sample variances and means as well as checks of serial correlation.

Since there is, theoretically, a one to one mapping of uniform random numbers into the desired distribution, the properties of the generated sequence should be determined by those of the uniform random number generator used.

To obtain random numbers with the desired Pearson distribution, the original version of the program generates a uniform random number and begins at the zero end of the c.d.f. testing each value of it until finding the closest one to the given uniform random number. This value is the ordinate of the Pearson c.d.f. and the corresponding abscissa, being the required random number, is calculated.

This method requires, on the average, a very large number of tests especially for a J-shaped distribution and produces only about four hundred random numbers per minute. To increase the speed of generation, the program was modified so that it first determines the centiles of the c.d.f. and immediately jumps to the appropriate centile to begin its search for the ordinate of the c.d.f. The centiles are stored without requiring additional storage by sharing their locations with unused variables during this operation.

In the event equality of the c.d.f. with the uniform random number is not reached, linear interpolation is used between intervals of the c.d.f. for greater accuracy and the abscissa, which is the required random number, is calculated. This procedure produces more

than ten thousand random numbers per minute.

5.3 Operating Information

The options obtained for various values of the arguments N1 and N2 used in the call statement of PURGE2 are given in Table 3.

Table 3. Values of the Arguments for PURGE2

Value of N1	Action Taken
1	Read <u>*OPTION CARD</u> and take action prescribed by it, i.e. read data cards, fit Pearson distribution, and generate 0 to 100 random numbers.
2	Generate up to 100 random numbers from a distribution previously described in the same program under the N1 = 1 or N1 = 3 option.
3	Fit a new Pearson curve from moments supplied by calling program via the common statement and generate 100 random numbers from this distribution.

Value of N2	Action Taken
1	Summations of first four powers of all numbers generated from this distribution are kept for later calculation of sample moments.
2	Summations of first four powers of all numbers generated from this distribution are used to calculate sample moments which are then printed.
3	The c.d.f. is punched on cards in binary along with necessary parameters for generating random numbers from this distribution then the same action is taken as for N2 = 2.
4	Same action is taken as for N2 = 2, then a graph of the distribution is printed. (Must be last option taken for a given distribution.)
5	Random numbers are generated without calculating summations for computation of moments. (Moments should not be printed for a given distribution after this option is used.)

5.31* Data Input Options

For each fit under the N1 = 1 option, the following format applies:

The first data card to be read is the *OPTION CARD.

Table 4. Option Card Format

Cols.	Option	Description
1		*ASTERISK
2-3		Blank
4-6	Input Format Option	There are two types of input: <u>four moments</u> describing the distribution or an actual sampling of the distribution. To specify that the input is the four moments on the next card (see formats) punch <u>-99</u> in this field. To specify <u>sampling data</u> in the built-in format, this field is <u>left blank</u> . To specify user's format (which is to be given on the next data card) a <u>positive integer</u> is placed in this field. (This integer is equal to the number of entries per card or record of input - up to 30 per card or record.) The computer run may be terminated by placing <u>999</u> in this field.
7-9		Blank
10-15	Input Number Option	There are two ways to specify the number of data entries of the sampling type. One is to enter the number of entries into this field. (The number of entries on the last card or record will be computed automatically.) The other is to place, on the end of the data, a record in which some two characters (columns) indicate the number of entries in the last entry card. (The remainder of that card should be blank.) This last method is indicated by leaving this field blank. For further clarification refer to the <u>INPUT FORMAT CARD</u> .

* This section is a modified version of the writeup of PURGE given by Cooper, Davis and Dono (1963).

Table 4, ctd.

Cols.	Option	Description
16-18		Blank
19-24	Output Generation Specifier	The number of random numbers to be generated per call (1-100) is specified in this field. The optimum efficiency is obtained at 100. If blank, only the fit will be obtained.
25-27		Blank
28-30	Force Fit Option	This field enables the user to override the usual Pearson criterion and force the fit to a specific Type. If this field contains a one, four, six or the integer 999, the Pearson Type One, Four, Six or Normal, respectively, will be used to fit the data. If blank, the usual Pearson criterion is used.
31-33		Blank
34-35	Input Tape Option*	If the user wishes to designate an input unit other than the normal card input, he may enter the symbolic tape unit in this field. If not, leave blank. (For moments and data points only.)
36-80		Blank

If the optional format control is desired for this fit, the next card should be the INPUT FORMAT CARD. This card is omitted if the optional format control is not used.

INPUT FORMAT CARD:

The optional format, when it is needed as indicated in columns 4-6 of the *OPTION CARD, must be described on this one card. It must take the same form as a source program FORMAT statement except that

* Requires a IBM 7040 with 32K core.

the word format is omitted. It may be punched in columns 1-72. Regardless of the format used, two characters (columns) of the record (card) - characters to the right of data - must be reserved since this format also reads in the END OF DATA CARD. Therefore, all INPUT FORMAT CARDS will end with I2 conversion. For example: to read in input data four to the record, the following format might be used; (4X,4F17.8,6X,I2) - this particular format represents the built-in format used if the optional format is not elected. It reserves columns 79 and 80 for the two characters of the END OF DATA CARD. (Note: use only F or E conversions.)

The next card or cards should be the MOMENT CARD (or record) or DATA POINT CARDS (or records) depending on which option is chosen.

MOMENT CARD:

The first four moments are specified on the MOMENT CARD in four fields as outlined in Table 5.

Table 5. Moment Card Format

Variable Name	Cols.	Description
	1-4	- Blank
AVE	5-21	- Mean or first moment about zero
CM2	22-38	- Variance or second central moment
CM3	39-55	- Skewness or third central moment
CM4	56-72	- Kurtosis or fourth central moment
	73-80	- Blank

The format for each moment is F17.8, a 17 digit floating point number.

DATA POINT CARDS:

The DATA POINT CARDS (or records), used if the input is not moments, have the same format as the MOMENT CARD above when using the built-in format. Two columns to the right of the entries (columns 79 and 80 in the built-in format) must not be used since the same format reads in the END OF DATA CARD. (Refer to INPUT FORMAT CARD.)

If the sampling data input is used, and the Input Number Option is not used, i.e. columns 10-15 on the *OPTION CARD are blank, the next card must be the END OF DATA CARD. This card is omitted when the Input Number Option is used or if sampling data input is not used.

END OF DATA CARD:

The END OF DATA CARD is used to indicate the end of the sampling data input entries when the Input Number Option is not used. It is a blank card except for the two columns which contain an integer specifying the number of entries on the last DATA POINT CARD. These two columns are specified on the INPUT FORMAT CARD. (Built-in format uses 79-80.)

5.32 Parameter Options

There are several other options available through the arguments N1 and N2 which deserve special attention.

The random numbers are returned to the calling program as implied arguments by the use of the FORTRAN common statement. The sequence of instructions

```
COMMON/Z2/RDS(100)
.
.
.
CALL PURGE2(1,1)
```

would cause PURGE2 to read data cards, fit a distribution with generation of up to 100 random numbers in the array RDS and exit, printing only the type of distribution fitted along with its parameters. The array in block Z2 must always be dimensioned at 100 even though fewer numbers may be generated per call as specified in columns 19-24 of the *OPTION CARD.

If the next call to PURGE2 is

```
CALL PURGE2(2,1)
```

another batch of up to 100 random numbers, from the same distribution, is stored in RDS without printing anything. This batch of random numbers represents a continuation of the sequence which began with the call with N1 = 1. If the graph of the distribution is desired along with the moments

```
CALL PURGE2(2,4)
```

should be the last call to PURGE2 for this distribution. This call will cause PURGE2 to generate another batch of random numbers placing them in RDS and to print the moments followed by the graph of the distribution. Since the graph routine shares storage with the c.d.f., hence destroying it, further generation can not be made from this distribution without refitting it.

In some cases, it is desirable to fit a distribution without reading input from cards. The following sequence of instructions will

cause a Pearson distribution to be fitted and 100 random numbers to be generated in RDS, printing only the type of curve fitted along with its parameters.

```
COMMON/Z1/AVE/Z2/RDS(100)/Z9/CM2,CM3,CM4,BETA1,BETA2,SKAPPA
.
.
.
AVE = 0.    (mean)
CM2 = 1.    (variance)
CM3 = 0.    (third central moment)
CM4 = 3.    (fourth central moment)
CALL PURGE2(3,1)
```

This particular case represents a $N(0,1)$ distribution. Other distributions may be generated by inserting the proper moments.

If the next call to PURGE2 is

```
CALL PURGE2(2,3)
```

another batch of 100 random numbers, with the same distribution, will be placed in RDS, a binary deck of about 100 cards will be punched and the moments printed. This binary deck may be used as input to the MIX subroutine which generates mixtures of distributions as is discussed in Chapter VI.

If PURGE2 is called with $N2 = 5$, random numbers are generated about twice as fast by not calculating moments from them. If the moments calculated from the numbers generated up to this point are desired, they must be printed before this option is taken as they will be incorrect in any subsequent printout after this option is used.

5.33 Regeneration

Occasionally, it may be desired to regenerate a sequence of

random numbers or continue from the same sequence in a different computer run.

This can be accomplished by modifying the uniform random number generator used.* The instructions

```
COMMON/VPI001/NUMBR  
  
NEXT = NUMBR      (store starting value of uniform  
                  random generator)  
  
CALL PURGE2(1,1)  (generate numbers)  
  
NUMBR = NEXT      (set starting value of uniform  
                  generator to its initial value)  
  
CALL PURGE2(2,1)  (generate same numbers)  
  
WRITE(7) NUMBR    (punch binary card with starting  
                  number for uniform random number  
                  generator)
```

in the control program will store the starting value of the uniform random number generator and reset it to its original value when it is desired to regenerate the numbers. Here the last value of NUMBR is punched on a card in binary and may be used as input in a later computer run to continue the sequence at the point it was terminated. The common statement must be used whenever NUMBR is modified.

The instructions

```
COMMON/VPI001/NUMBR  
  
READ(5) NUMBR  
  
CALL PURGE2(1,1)  (generate numbers)
```

* These modifications apply only to the random number generator used at the VPI Computing Center.

in the control program will continue the uniform random number sequence in a different computer run when used with the binary card output from a preceding run.

Note that the sequence of uniform random numbers generated will always be the same in different computer runs since the initial value of NUMBER is always zero. If desired, this difficulty may be overcome by setting NUMBER equal to some different arbitrary value at the beginning of each computer run. The COMMON statement must be used when this is done. All sequences of uniform random numbers which begin with the same value of NUMBER will be identical.

5.34 Variables Available thru COMMON

Table 6 gives the names of variables used in PURGE2 which may be placed in COMMON with the calling program along with their block name and use in PURGE2.

As an example of how these variables may be used, suppose the programmer wished to fit a Pearson distribution with PURGE2 and then make a test on Pearson's K in the calling program. The instructions

```
COMMON/Z9/CM2,CM3,CM4,BETA1,BETA2,SKAPPA
```

```
CALL PURGE2(1,1)
```

```
IF(SKAPPA .EQ. 0.) XYZ = 0.
```

would set XYZ equal to zero if $K = 0$.

Table 6. Variables in PURGE2 Available thru COMMON

Block	Variable	Use
Z1	AVE	Mean of Pearson distribution
Z2	TOM(100)	Array used to store generated random numbers
Z3	LIMIT	Number of random numbers to be generated per call (0-100)
Z4	FA(4)	Noncentral moments calculated from generated data*
Z5	FAN(4)	Sums of first four powers of generated numbers*
Z6	N	Number of intervals of the c.d.f.**
Z7	KU(101)	Centile index for c.d.f.**
Z8	S(2641)	c.d.f.**
Z9	OM2	Variance of Pearson distribution
	OM3	Third moment of Pearson distribution
	OM4	Fourth moment of Pearson distribution
	BETA1	β_1 of Pearson distribution
	BETA2	β_2 of Pearson distribution
	SKAPPA	κ of Pearson distribution
Z10	FCM2	Variance of generated numbers*
	FCM3	Third moment of generated numbers*
	FCM4	Fourth moment of generated numbers*
	FBETA1	β_1 of generated numbers*
	FBETA2	β_2 of generated numbers*
	FKAPPA	κ of generated numbers*

* Not calculated for fast generation option.

** Not calculated unless random number generation is required.

5.35 Error Conditions

In the event that an error condition develops when fitting a curve, a diagnostic message is printed, LIMIT is set to zero and the subroutine exits normally. One such error condition arises when illegal values are obtained for β_1 and β_2 . The values of β_1 and β_2 are restricted to a certain domain for distribution functions. The shaded portion of Figure 1 indicates the domain of these parameters.

It is the responsibility of the programmer to test for an error condition after the first call to PURGE2 for a given distribution.

This may be done by the following sequence of instructions

```
COMMON/Z3/LIMIT
.
.
.
CALL PURGE2(N1,N2)

IF(LIMIT .EQ. 0) (error, PURGE2 is unable to fit
.               this distribution and calling
.               program should skip to the next
.               fit or stop)
```

This test should only be made when attempting to generate and use random numbers not when LIMIT should be zero as is the case when only a fit is required.

It is possible that overflow conditions may occur either in computing moments from sampling data or in computing moments from generated data. Since both underflows and overflows occur as normal conditions in the program, it operates under no limit on underflow or overflow conditions. No warning is given when normal underflows or overflows occur.

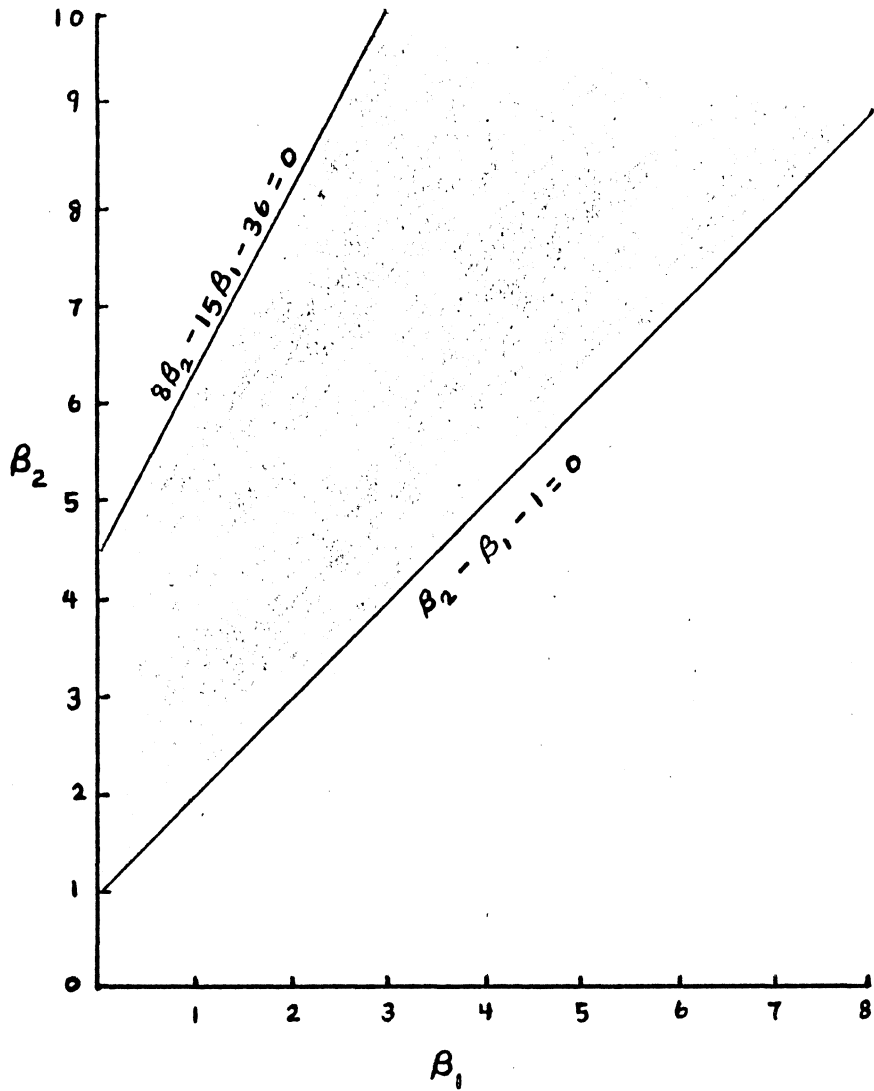


Figure 1. Admissible Region For β_1 and β_2 .

The program tests for overflow when computing moments and should overflow occur when computing moments from data, LIMIT is set to zero (as a warning to calling program that PURGE2 was unable to fit a curve) and the diagnostic "TOO MUCH AND / OR TOO LARGE DATUM" is printed. Should an overflow occur during the computation of moments from generated data, "OVERFL" is printed before printing moments as a warning that the moments from the generated data are incorrect, otherwise the program functions normally. Note, it is the responsibility of the programmer to test for overflow or underflow conditions which may occur in his program since it will also operate with no limit on overflow or underflow conditions. A flowchart of the PURGE2 subroutine and a FORTRAN IV listing for an IBM 7040 are given in the Appendix.

5.4 Sample Input and Output

The following computer program

```
COMMON/Z1/AVE/Z2/RDS(100)/Z9/CM2,CM3,CM4,BETA1,BETA2,SKAPPA
CALL PURGE2(1,4)
CALL PURGE2(1,4)
AVE = 50.
CM2 = 1.
CM3 = 2.
CM4 = 9.
CALL PURGE2(3,4)
STOP
END
```

(DATA see figure 2)

when used with the input data given in Figure 2 and the PURGE2 subroutine will produce Figures 3-5. Figure 6 illustrates the data deck for a fit from sampling data. Figure 7 gives a force fit of the normal distribution from the given moments. Figure 8 illustrates a data deck

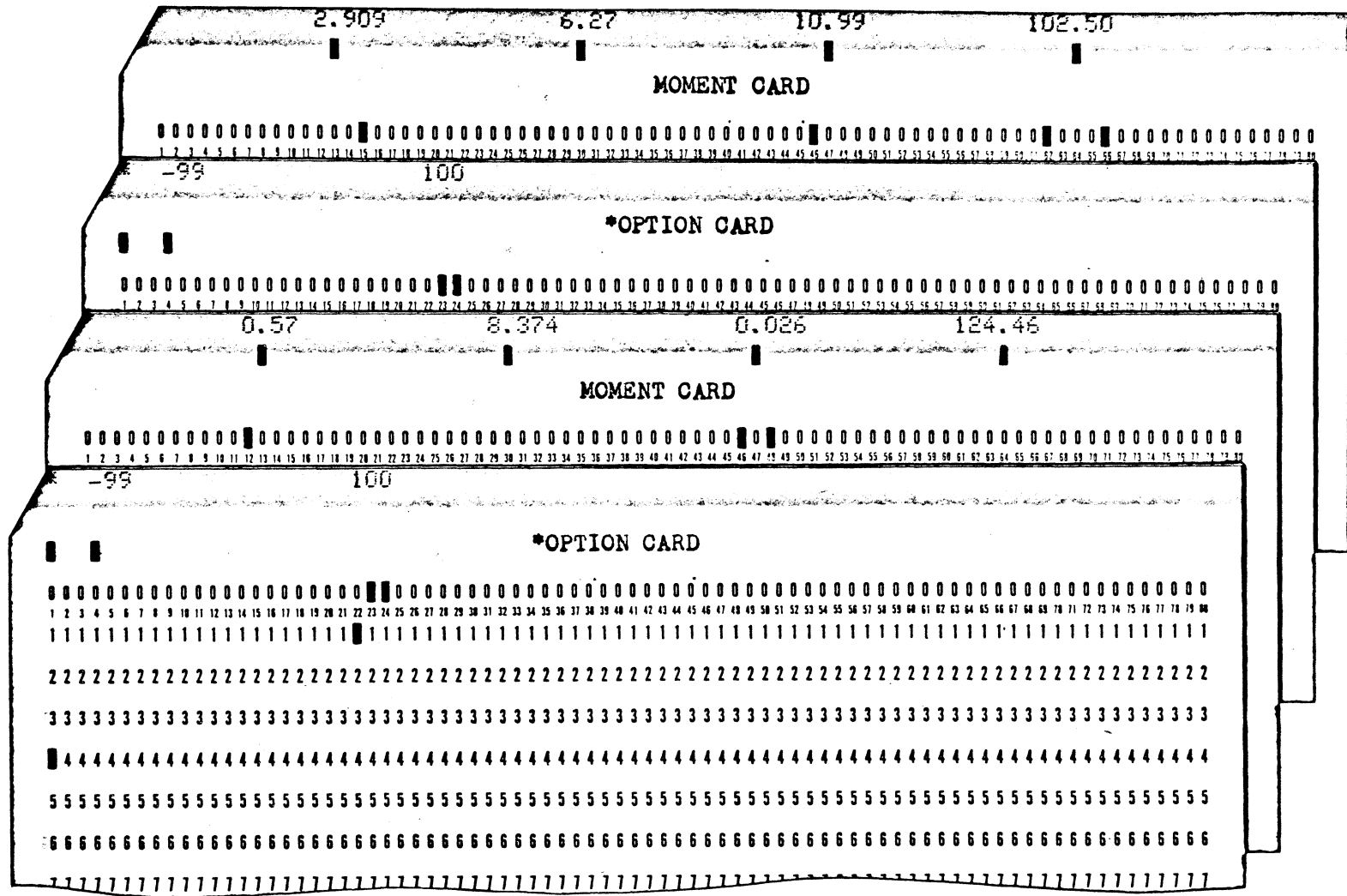


Figure 2. Moment Card Input

PEARSON CURVE TYPE ONE

DISTRIBUTION GENERATOR

M1=-1.08489E-01 M2= 1.08078E 00 A1= 3.26667E 00 A2= 7.62436E 00 YE= 1.24426E-01

MOMENTS	FROM ORIGINAL DATA	FROM GENERATEI DATA	N=
MEAN	2.90900000	2.43103834	100
VARIANCE	6.26999992	5.31912140	
MU(3)	10.99000000	14.08958480	
MU(4)	102.50000000	110.11172096	
BETA 1	0.48999626	1.31909683	
BETA 2	2.60728668	3.89182892	
KAPPA	-0.19060951	-0.62067799	

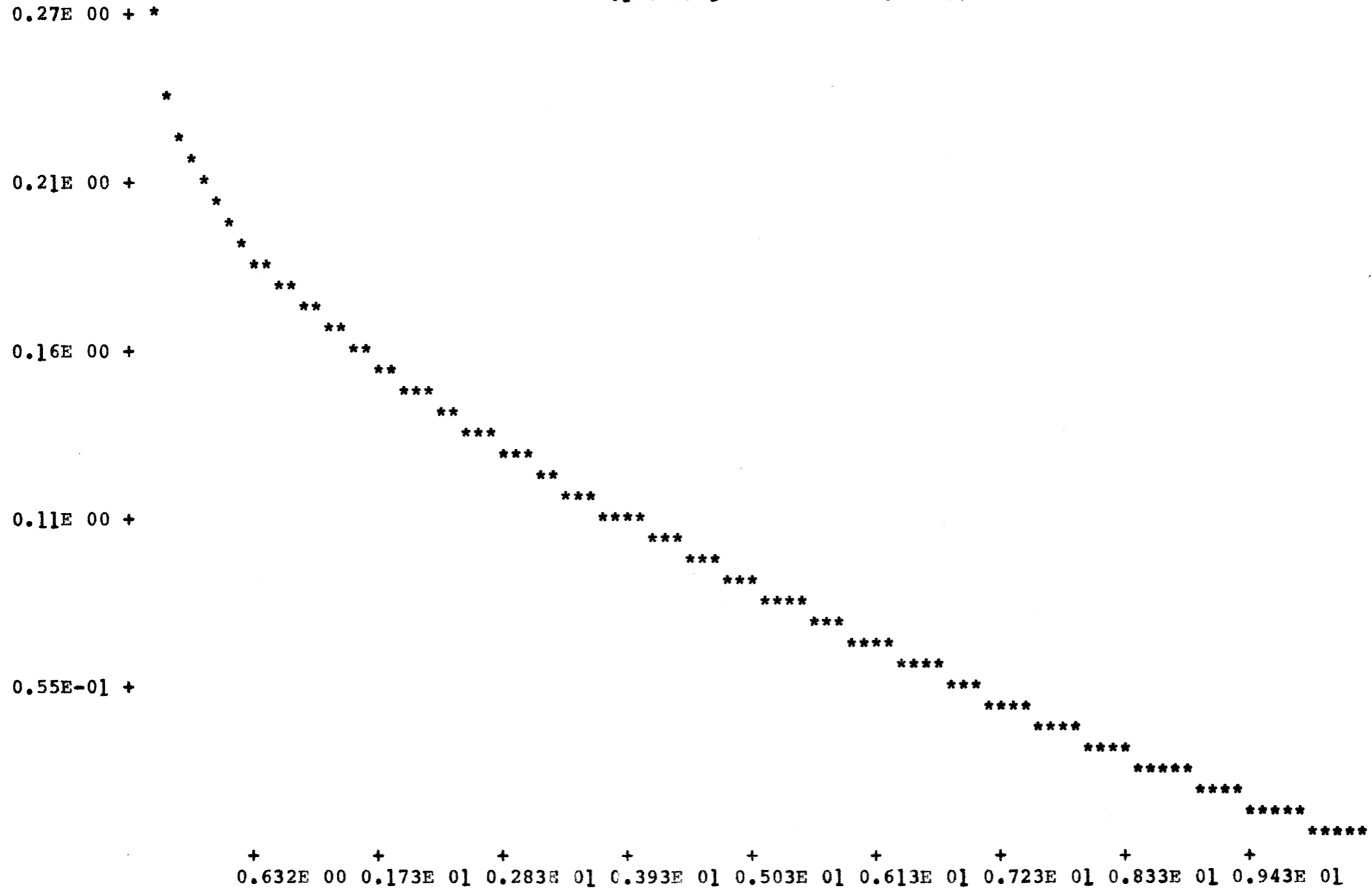


Figure 4. PURGE2 Output

SUBCLASS TYPE TEN

DISTRIBUTION GENERATOR

G= 1.00000E 00 P= 0.

A= 1.00000E 00 YE= 3.67279E-01

MOMENTS FROM DATA

MEAN	50.00000000
VARIANCES	1.00000000
MU(3)	2.00000000
MU(4)	9.00000000
BETA 1	4.00000000
BETA 2	9.00000000
KAPPA	*****

(Asterisks indicate Kappa too large to be printed.)

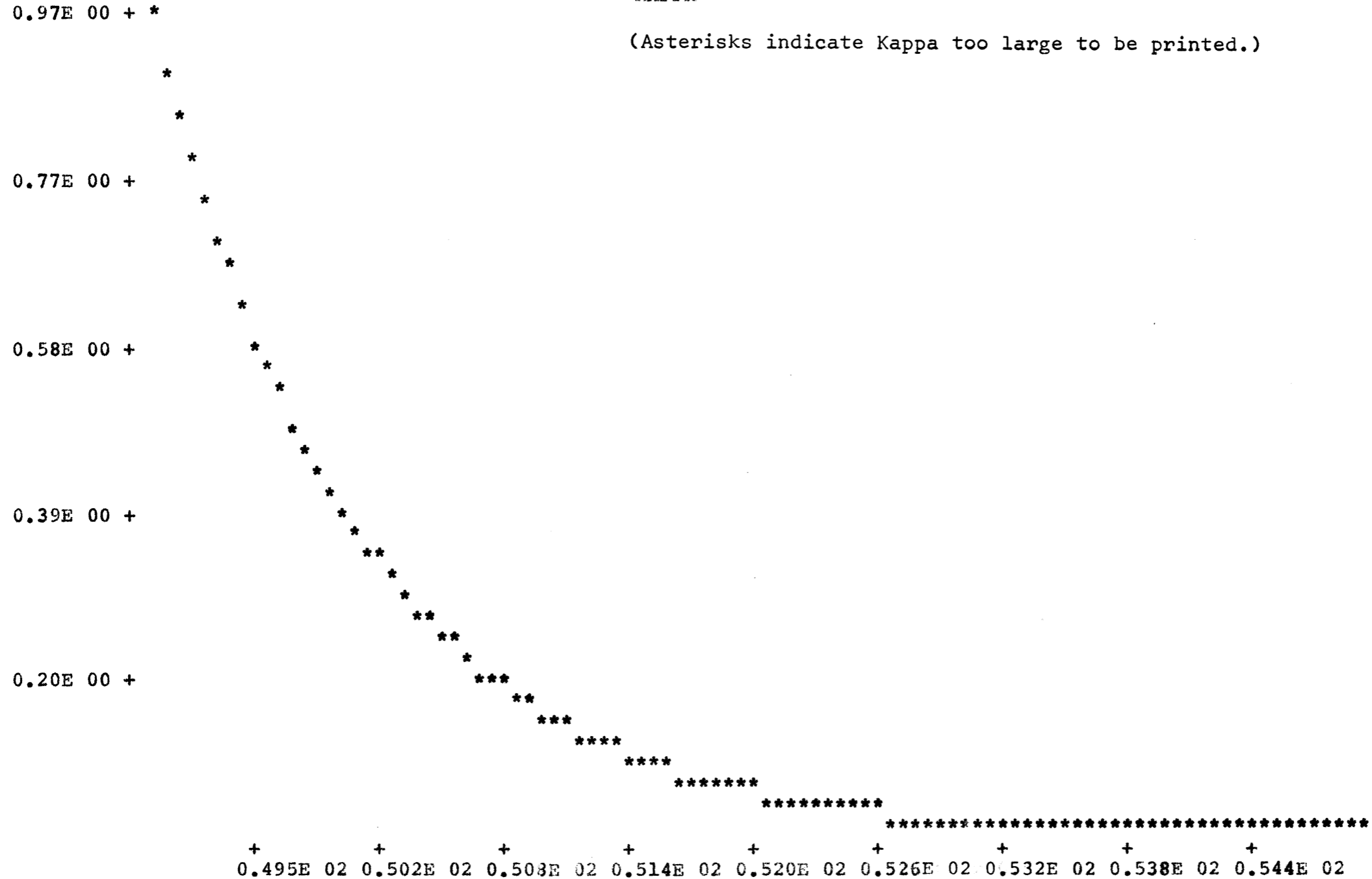


Figure 5. PURGE2 Output

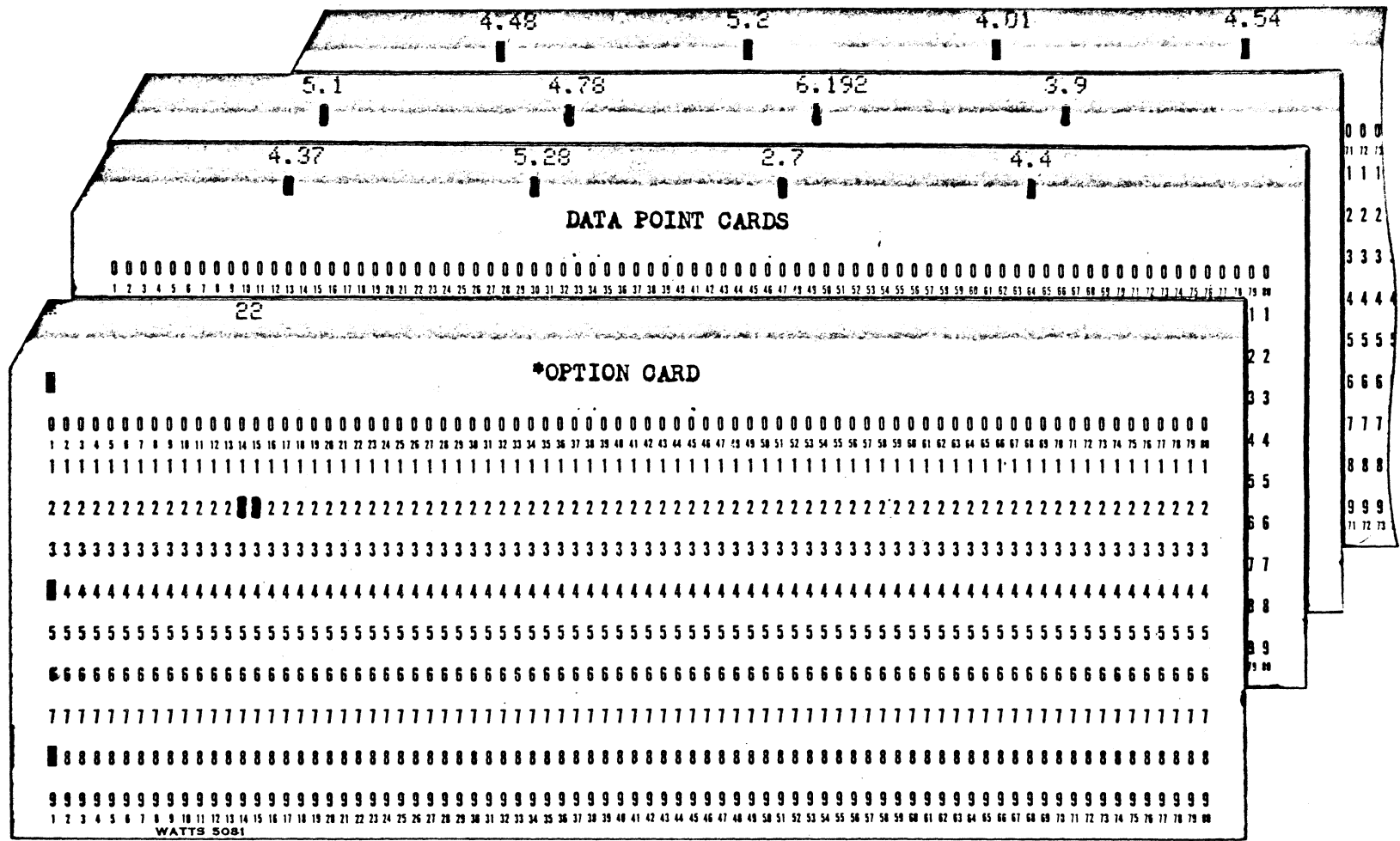


Figure 6. Data Point Card Input

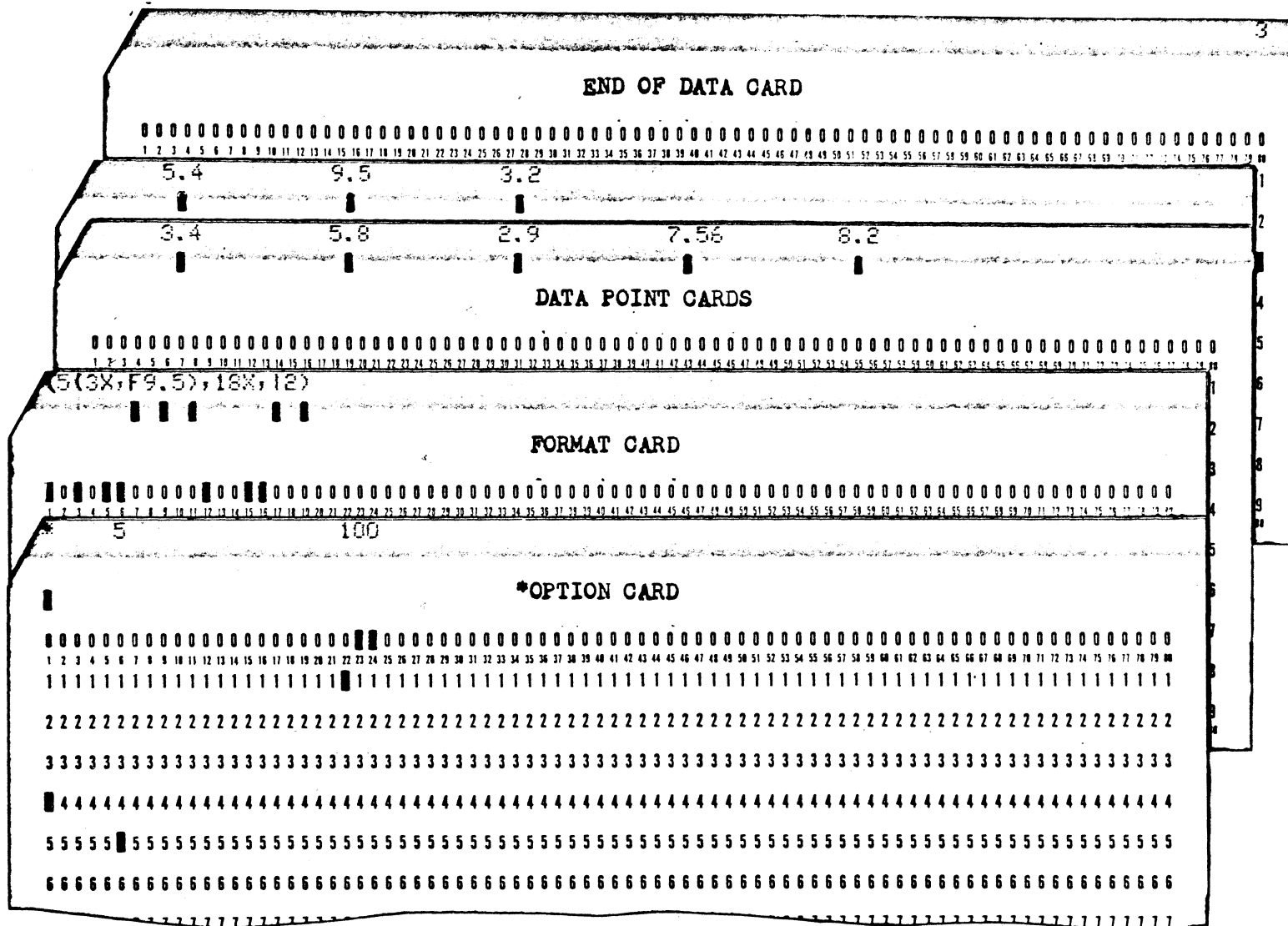


Figure 8. Data Point Card Input With Special Format

using the optional input format.

5.5 Tests of PURGE2

The performance of the aforementioned uniform random number generator is a major factor in the properties of the random numbers generated by PURGE2. Kaercher (1962) reports satisfactory statistical results were obtained from tests made on the uniform random number generator used in PURGE2 at the VPI Computing Center. See Section 5.2.

Several tests were made as a check on the performance of random numbers generated by PURGE2 and the results of all of them seem satisfactory.

Moments

For the χ^2 distribution (Pearson's Type III) with 10 d.f., 50,000 random numbers were generated and the calculated moments compared with the true moments as a check on convergence. Table 7 gives values of the mean as well as the second, third and fourth central moments in intervals of 10,000 and also the true moments.

Table 7. Values of Sample Moments from a χ^2_{10} Distribution

N	M'_1	M_2	M_3	M_4
10,000	10.0232	20.4682	85.5119	1737.8079
20,000	9.9809	20.4682	81.0195	1667.2398
30,000	9.9778	20.0569	81.2117	1675.9766
40,000	9.9638	19.9039	80.0241	1642.7236
50,000	9.9787	19.9659	79.6566	1634.1745
True	10.0000	20.0000	80.0000	1680.0000

These data suggest that the moments are converging to their true values. The sampling variability is, of course, larger in the higher order moments. Tables 8, 9, and 10 are obtained from the generation of 12,000 numbers from each of three Pearson Type I distributions being bell, J and U shaped respectively. Note, the graph of the distribution used in Table 9 appears as Figure 3 whereas that of Table 10 is Figure 4.

Table 8. Values of Sample Moments from a Bell Shaped Type I Distribution

N	M_1'	M_2	M_3	M_4
3,000	0.070	30.207	207.136	4728.115
6,000	0.093	31.242	221.975	5101.772
9,000	0.052	30.411	204.544	4627.790
12,000	0.0002	29.734	194.979	4352.521
True	0	29.501	190.112	4361.120

Table 9. Values of Sample Moments from a J-Shaped Type I Distribution

N	M_1'	M_2	M_3	M_4
3,000	0.508	8.824	2.633	143.696
6,000	0.597	8.819	1.878	142.630
9,000	0.593	8.805	1.864	142.416
12,000	0.571	8.803	2.193	142.762
True	0.570	8.374	0.026	142.460

Table 10. Values of Sample Moments from a U-Shaped Type I Distribution

N	M_1	M_2	M_3	M_4
3,000	2.915	6.307	11.254	103.673
6,000	2.925	6.287	11.040	103.028
9,000	2.901	6.129	10.699	99.112
12,000	2.898	6.115	10.687	98.734
True	2.909	6.270	10.990	102.500

Some alternative tests which could be used on PURGE2 are χ^2 goodness of fit tests, the Kolmogorov statistic and testing random numbers on a similar problem for which the answer is known. It should be noted that the results of tests on runs up and down made on the uniform random number generator carry over directly here because of the one to one correspondence of the uniform random numbers with those from a Pearson distribution using this method of generation.

The following remarks made by Hull and Dobell (1964) seem appropriate here. ". . . no finite class of tests can guarantee the general suitability of a finite sequence of (random) numbers. Given a set of tests, there will always exist a sequence of numbers which passes these tests but which is completely unacceptable for some particular application.

The point is that the appropriate tests are entirely dependent on the application for which the random numbers are needed."

VI. MIX SUBROUTINE

The MIX subroutine was written to overcome the limitation, inherent in PURGE2, of being restricted to generating only unimodal Pearson distributions. Under certain conditions, this subroutine will generate random numbers from continuous distributions of almost any shape at speeds up to ten times faster than PURGE2, i.e. more than 100,000 random numbers per minute on the IBM 7040. This great increase in speed is accomplished by using large proportions of uniform and normal random numbers in the mixtures since these may be generated much faster than the Pearson types. The speed of generation increases as the proportion of uniform and normal numbers in the mixture increases.

6.1 Description and Purpose

The greater flexibility in the shape of distributions which may be generated by the MIX subroutine is achieved by a probability mixture of any combination of one or two Pearson distributions with a uniform distribution, on any interval, and also a normal distribution with any mean and variance.

The desired Pearson distributions are generated by PURGE2 and cards containing the c.d.f. along with the necessary parameters for generating random numbers are punched in binary for later input to MIX. (Both programs, written in FORTRAN IV, could be combined on a 32K IBM 7040 system to eliminate the card input-output for greater efficiency.)

A control card specifying the proportions of the various dis-

tributions to be mixed followed by the cumulative distribution functions of the Pearson distributions is then fed in as input to MIX. Using the c.d.f. of the desired Pearson distribution, MIX is able to generate random numbers from that distribution in the same way as FURGE2. The proportion of distributions mixed may later be modified by the control program. The MIX subroutine may also be used to generate random numbers from a single Pearson distribution without refitting the curve for each computer run.

Output options included printing theoretical moments along with moments computed from the generated numbers and also a graph of the distribution.

6.2 Method

The density function f of a random variable x , which we wish to generate, may be represented by

$$f(x) = \sum_{i=1}^4 a_i f_i(x)$$

where each f_i is a density function and a_i is the probability of

obtaining x from f_i where $\sum_{i=1}^4 a_i = 1$, $a_i \geq 0$ all i .

To obtain the moments of f , we have

$$EX^r = \int_R x^r f(x) dx = \sum_{i=1}^4 a_i \int_{R_i} x^r f_i(x) dx$$

where R_i is the domain of definition of f_i whereupon

$$EX^r = u_r^i = \sum_{i=1}^4 a_i u_{R_i}^i .$$

The MIX subroutine first computes the moments about zero for each distribution, multiplies them by the appropriate probability, sums them and converts the second thru fourth moments to central moments.

For random number generation, the program generates a uniform (0,1) random number which determines the distribution from which to generate x with distribution f. To illustrate the procedure suppose we have

$$f(x) = .50f_1(x) + .25f_2(x) + .20f_3(x) + .05f_4(x) .$$

A uniform random variable u is generated. If $u < .50$, x is generated from distribution f_1 ; if $.50 \leq u < .75$, x is generated from f_2 ; if $.75 \leq u < .95$, x is generated from f_3 ; and if $.95 \leq u < 1$, x is generated from f_4 . After x has been generated, this process is repeated 100 times per call to MIX and if required, moments are calculated from the generated numbers for comparison with their theoretical values.

The speed of generation, in numbers per minute on the IBM 7040 using the uniform and normal random number generators available at the VPI Computing Center, is approximately given by

$$n = 10^4(a_1 + a_2) + 3 \times 10^4 a_3 + 10^5 a_4$$

where a_1 and a_2 represent probabilities of generating from Pearson distributions, likewise a_3 for the normal and a_4 the uniform. If the a_i are chosen such that a_1 and a_2 are small in comparison with a_3 and a_4 as suggested in papers by Marsaglia (1961 and 1964), very fast methods of generation are obtained.

If desired, a graph of the density function may be obtained from

10,000 random numbers with the required distribution. The numbers are first generated to determine their range. The range is then divided into 100 equally spaced intervals and the numbers are regenerated to determine the frequency in each interval.

At this point an option to smooth the data, using moving averages of order five may be elected. In order not to drop the first two and last two points of the curve, using this method, the first and last points remain unchanged whereas the second and 99th points are determined from

$$x_2 = (x_1 + x_2 + x_3)/3, \quad x_{99} = (x_{98} + x_{99} + x_{100})/3 .$$

This technique is used to preserve the end points of J and U shaped distributions and appears to give good results.

By summing the area of the 100 rectangles and requiring it to be unity, an ordinate scale is obtained whence the curve is plotted. The scale is more accurately determined if smoothing is used.

6.3 Operating Information

The MIX subroutine is entered by the FORTRAN statement

```
CALL MIX(N1,N2)
```

where N1 and N2 are arguments which describe the option desired.

The options obtained for various values of the arguments are given in Table 11.

Table 11. Values of the Arguments for MIX

Value of N1	Action Taken
1	Read <u>CONTROL CARD</u> and if necessary binary cards for Pearson distribution(s). Generate 100 random numbers from the mixture.
2	Generate 100 random numbers from a mixture of distributions previously described under the N1 = 1 option.

Value of N2	Action Taken
1	Summations of first four powers of all numbers generated from this mixture are kept for later calculation of sample moments.
2	Summations of first four powers of all numbers generated from this mixture are used to calculate sample moments which are then printed.
3	Same action is taken as for N2 = 2, then a graph of the mixture of distributions without smoothing is printed. (Must be last option taken for a given distribution.)
4	Same as for N2 = 3 except that a graph with smoothing is printed. (Must be last option taken for a given distribution.)
5	Random numbers are generated without calculating summations for computation of moments.

6.51 Data Input Option

For each fit under the N1 = 1 option the following format applies:

The first data card to be read is the CONTROL CARD followed by up to two binary decks produced by PURGE2. If more than one fit per run is desired, the next card would be a new CONTROL CARD followed by the necessary binary decks.

CONTROL CARD

The CONTROL CARD format is given in Table 12. The format for

probabilities is F7.4, a seven digit floating point number. The format for the other variables is F10.5, a ten digit floating point number.

Table 12. Control Card Format

Variable Name	Cols.	Description
P(1)	1-7	- Probability of selection of first Pearson distribution. (The computer run may be terminated by placing a floating point number greater than one in this field.)
P(2)	8-14	- Probability of selection of second Pearson distribution.
G	15-21	- Probability of selection of normal distribution.
GM	22-31	- Mean of normal distribution.
GV	32-41	- Variance of normal distribution.
U	42-48	- Probability of selection of uniform distribution.
UL	49-58	- Lower endpoint of uniform interval.
UP	59-68	- Upper endpoint of uniform interval.
	69-80	- Blank.

Note: If there is a number greater than zero but less than one in P(1) or P(2) then a Pearson binary deck produced by PURGE2 must follow the control card. If both are non-zero then two such decks must follow the control card.

6.32 Regeneration

When it is desired to regenerate a sequence of random numbers or continue from the same sequence in a different computer run, the

uniform random number generator must be modified in the manner described in Section 5.33. In addition, the normal distribution generator must be modified if it is used.

The normal random number generator used at the VPI Computing Center was developed and tested by Marsaglia, MacLaren and Bray (1963). It may be modified by placing the following FORTRAN cards in the calling program:

```
COMMON/VPI001/NUMBR/Z11/Q
NEXT = NUMBR           (store starting value of uniform
                        generator)
Q = RNEX(DUMMY)        (store starting value of normal
                        generator)
CALL MIX(N1,N2)        (generate numbers)
NUMBR = NEXT           (reset uniform generator to its
                        original starting value)
DUMMY = RNST(Q)        (reset normal generator to its
                        original starting value)
CALL MIX(N1,N2)        (regenerate numbers)
Q = RNEX(DUMMY)        (store starting value for normal
                        generator, needed to continue
                        sequence from this point)
WRITE(7) NUMBR, Q      (punch binary card with starting
                        values of uniform and normal gen-
                        erators which will continue se-
                        quence from this point)
```

If it is desired to continue the same sequence in a different computer run, the instructions

```
COMMON/VPI001/NUMBR/Z11/Q
READ(5) NUMBR, Q      (read binary card, punched in pre-
                        vious run, containing starting
```

values of uniform and normal generators needed to continue sequence)

DUMMY = RNST(Q)

(set normal generator to its starting value)

CALL MIX(N1,N2)

(continue generation)

placed in the calling program will cause the binary card punched in the previous run to be read and the sequence of random numbers to be continued from the point at which it was terminated.

6.33 Variables Available thru COMMON

The calling program may also modify the CONTROL CARD variables by using the FORTRAN COMMON statement. See Table 13 for names and block numbers of variables available thru COMMON.

6.34 Error Conditions

The MIX subroutine tests the probability multipliers (no check is made for erroneously punched negative values) of the distributions to make sure they sum to one. They are rejected if their sum differs from one by as much as 0.001 in absolute value. If this condition exists, LIMIT is set to zero and may be tested in the same manner as in PURGE2. The subroutine exits printing the diagnostic message "MPYRS DO NOT SUM TO 1, REQ FOR DIST FUN".

Overflow when computing moments from generated data is handled in the same way as in PURGE2 (see Section 5.35).

A flowchart of the MIX subroutine and a FORTRAN IV listing for an IBM 7040 are given in the Appendix.

Table 13. Variables in MIX Available thru COMMON

Block	Variable	Use
Z1	TM1	Theoretical mean of mixture
Z2	TOM(100)	Generated random numbers
Z3	LIMIT	Number of random numbers to be generated per call (100)
Z4	FA(4)	Noncentral moments calculated from generated data*
Z5	FAN(4)	Sums of first four powers of generated numbers*
Z6	N(2)	Number of intervals of the c.d.f.
Z7	KU(2,101)	Centile index for c.d.f.
Z8	S(2,2641)	c.d.f.
Z9	QM2	Theoretical variance of mixture
	QM3	Theoretical third moment of mixture
	QM4	Theoretical fourth moment of mixture
Z10	FCM2	Variance of generated distribution*
	FOM3	Third moment of generated distribution*
	FCM4	Fourth moment of generated distribution*
Z11	Q	Starting value for normal random number generator
Z12	P(1), P(2), G, GM, U, UL, UP	<u>CONTROL CARD</u> variables in the order they appear on it

* Not calculated for N2 = 5 option.

6.4 Sample Input and Output

The following computer program

```
COMMON/Z2/RDS(100)
CALL MIX(1,4)
CALL MIX(1,4)
STOP
END
```

(DATA see Figure 9)

when used with the input data given in Figure 9 produces Figures 10 and 11. Figure 10 is derived from a mixture of 30% of the U shaped distribution shown in Figure 3 and 70% $N(0,1)$. Figure 11 is a mixture of 25% each of a J shaped distribution with moments 0.051, 4.266, -7.688 and 48.154, the distribution shown in Figure 3 (U shape), $N(0,2)$ and uniform on $(-1,0)$. The smoothing option was used for both graphs.

Figure 12 is a graph of 10,000 observations from a $N(0,1)$ distribution without smoothing whereas Figure 13 is a graph of the same data with smoothing.

DISTRIBUTION MIXTURES

CONTROL CARD P1= 0.3000 P2= -0.0000 NORM= 0.7000 MEAN= -0.00000 VAR= 1.00000
 UNIF= -0.0000 FROM -0.0000 TO -0.0000

MOMENTS	FROM ORIGINAL DATA	FROM GENERATED DATA	N= 10000
MEAN	0.17100000	0.03850844	
VARIANCE	3.28042888	3.34579096	
MU(3)	2.67135952	2.14223446	
MU(4)	41.98112896	45.84792448	

0.34E 00 +

0.27E 00 +

0.20E 00 +

0.14E 00 +

0.68E-01 +

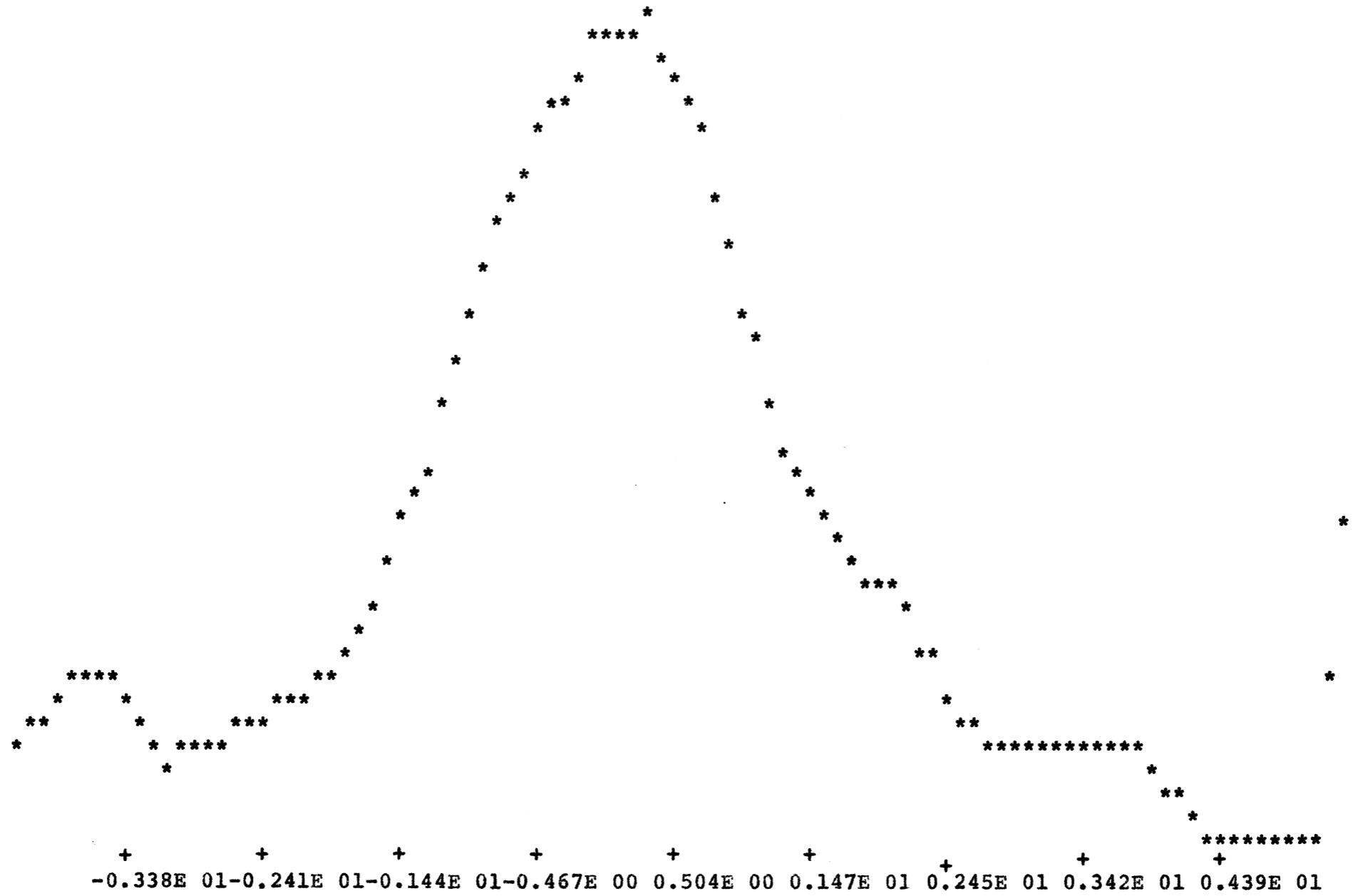


Figure 10. MIX Output

DISTRIBUTION MIXTURES

CONTROL CARD P1= 0.2500 P2= 0.2500 NORM= 0.2500 MEAN= -0.00000 VAR= 2.00000
 UNIF= 0.2500 FROM -1.0000 TO -0.0000

MOMENTS	FROM ORIGINAL DATA	FROM GENERATED DATA	N= 10000
MEAN	0.03025000	-0.00531474	
VARIANCE	3.82429340	4.12326840	
MU(3)	1.46430850	0.81013203	
MU(4)	49.75215488	57.12495424	

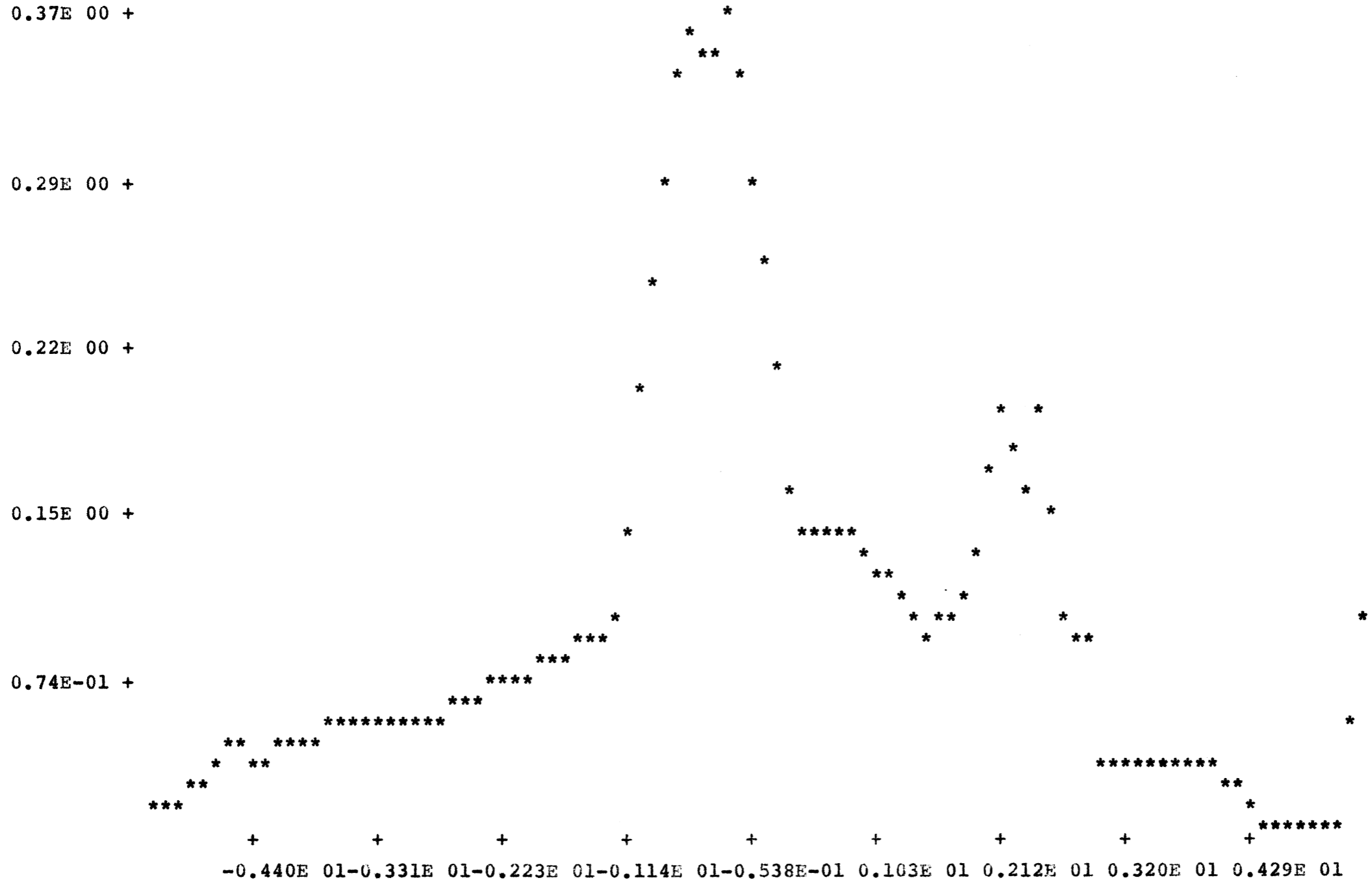


Figure 11. MIX Output

DISTRIBUTION MIXTURES

CONTROL CARD P1= -0.0000 P2= -0.0000 NORM= 1.0000 MEAN= -0.00000 VAR= 1.00000
 UNIF= -0.0000 FROM -0.0000 TO -0.0000

MOMENTS	FROM ORIGINAL DATA	FROM GENERATED DATA	N= 10000
MEAN	-0.00000000	0.04899041	
VARIANCE	1.00000000	0.97922736	
MU(3)	0.00000000	0.05991855	
MU(4)	3.00000000	2.78555760	

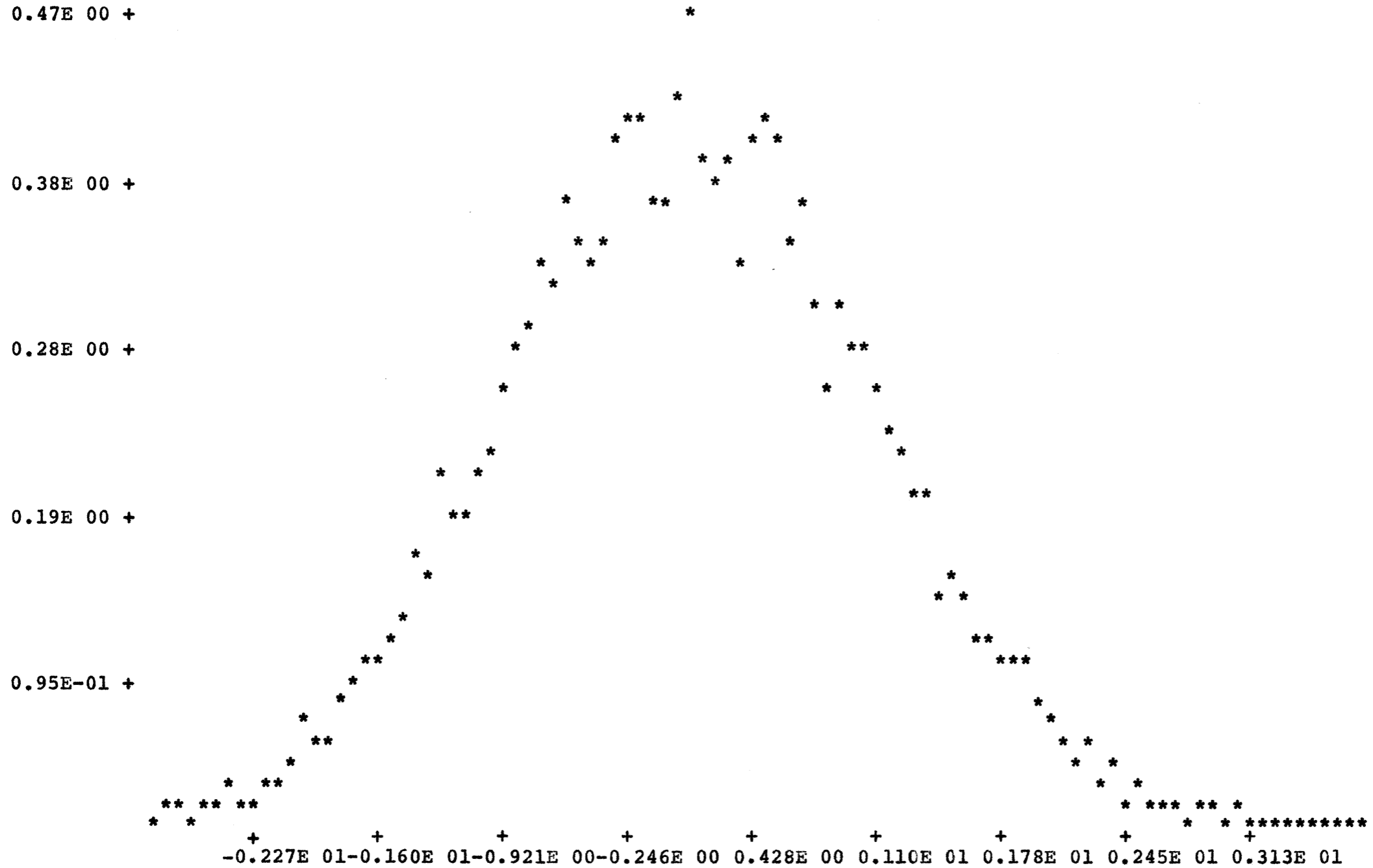


Figure 12. MIX Output

CONTROL CARD P1= -0.0000 P2= -0.0000 NORM= 1.0000 MEAN= -0.00000 VAR= 1.00000
 UNIF= -0.0000 FROM -0.0000 10 -0.0000

MOMENTS	FROM ORIGINAL DATA	FROM GENERATED DATA	N= 10000
MEAN	-0.00000000	0.04899041	
VARIANCE	1.00000000	0.97922736	
MU(3)	0.00000000	0.05991855	
MU(4)	3.00000000	2.78555760	

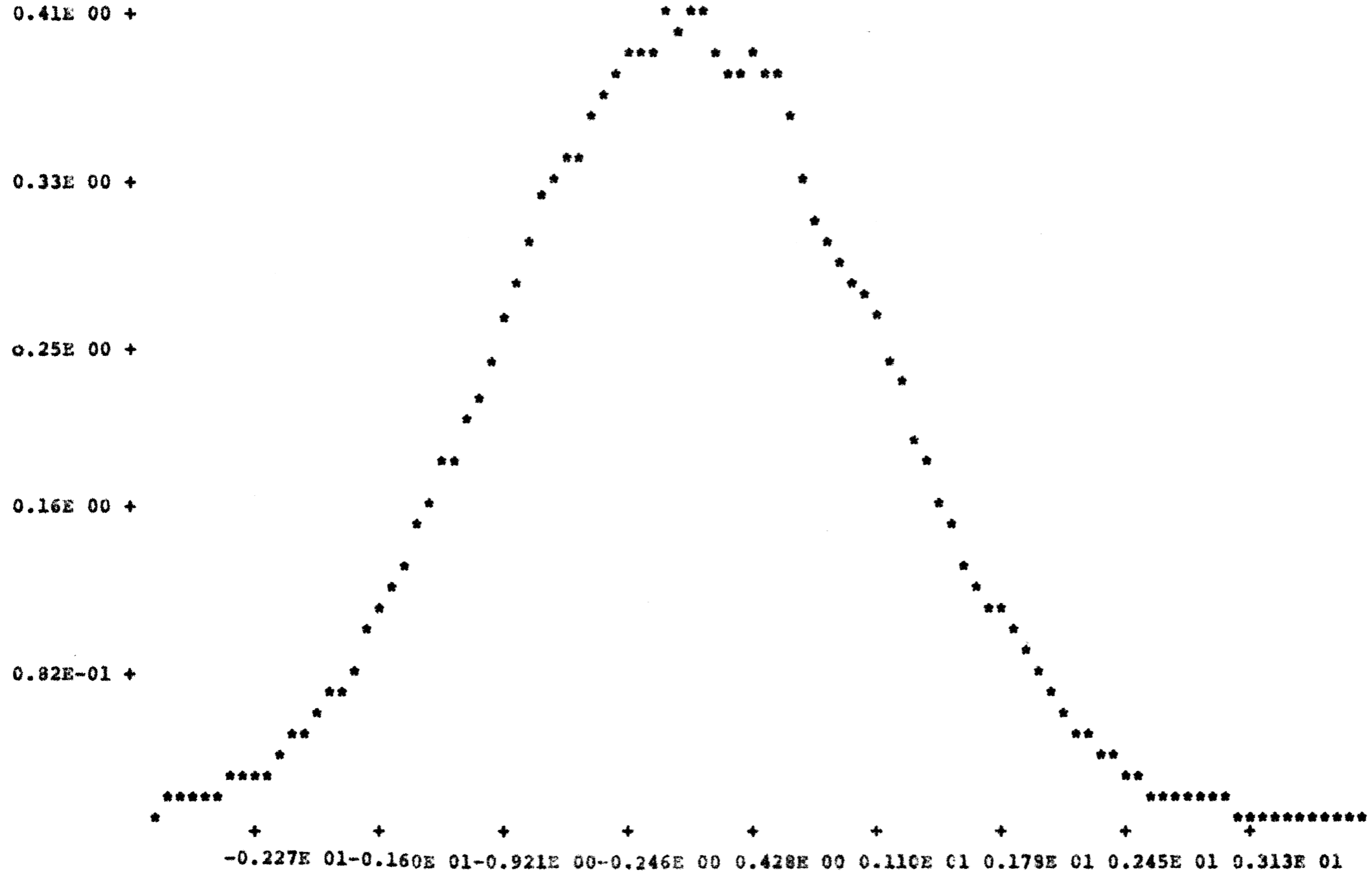


Figure 13. MIX Output

CONTROL CARD P1= 0.4000 P2= -0.0000 NORM= 0.4000 MEAN= 8.00000 VAR= 10.00000
 UNIF= 0.2000 FROM 8.0000 TO 10.0000

MOMENTS	FROM ORIGINAL DATA	FROM GENERATED DATA	N= 10000
MEAN	8.99999984	9.03124128	
VARIANCE	12.86666768	12.39445872	
MU(3)	44.00000000	41.10000608	
MU(4)	992.84007936	835.58983680	

0.20E 00 +

**
 ** *
 *

0.16E 00 +

0.12E 00 +

*

*

** *

0.80E-01 +

*

* *

*

*

0.40E-01 +

* *

**

*

*

*

*

**

* ***** *

+ + + + +
 0.197E 01 0.513E 01 0.830E 01 0.115E 02 0.146E 02 0.178E 02 0.210E 02 0.241E 02 0.273E 02

Figure 14. MIX Output

VII. APPLICATION TO INVESTIGATION OF ROBUSTNESS

7.1 Confidence Interval Problem

As a practical example of how the foregoing computer programs may be used, consider the problem of investigating the effects of departure from normality of the parent population on three methods of estimating confidence intervals for the mean μ with confidence coefficient $1 - \alpha$, where the true mean and variance are unknown.

7.2 Methods of Estimation

The methods of confidence interval estimation under consideration are:

- (1) the standard procedure using the sample standard deviation given by

$$(7.1) \quad \bar{x} \pm \frac{s}{\sqrt{n}} t_{(\alpha/2, n-1)}$$

where

$$s^2 = \sum_{i=1}^n (x_i - \bar{x})^2 / (n - 1)$$

and $t_{(\alpha/2, n-1)}$ is the appropriate percentage point of the t-distribution with significance level $\alpha/2$ and $n - 1$ degrees of freedom,

- (2) a procedure using the sample mean absolute deviation

$$(7.2) \quad \bar{x} \pm mK_{(\beta, n)}$$

where

$$m = 1/n \sum_{i=1}^n |x_i - \bar{x}|$$

is the sample mean absolute deviation of the sample of size n and $K_{(\beta, n)}$

is tabulated by Krutchkoff (1965) for $n = 3(1)10$, $\beta = .80, .90, .95, .99$ and $.999$,

(3) a procedure, described by Noether (1955), using the sample range

$$(7.3) \quad \bar{x} \pm g_{\alpha} R$$

where R is the range of the sample of size n and g_{α} is the critical value tabulated by Jackson and Ross (1955) for $n = 2(1)15$, $\alpha = .01, .05$, and $.10$.

These methods assume an independent sample of size n from a normal population and under these conditions it is well known in statistical theory that the method using the sample standard deviation gives the confidence interval with the shortest expected length. The sample standard deviation is however, somewhat difficult to calculate without the aid of some type of computing equipment.

The sample mean absolute deviation is much easier to calculate since no square roots are involved and Krutchkoff (1965) shows that the "sacrifice" or fractional increase in interval length is small being on the order of two to five percent except when an excessively high confidence on the basis of very few observations is desired. He also shows there is something to be gained by using the sample mean absolute deviation if one more observation is allowed than with the sample standard deviation. In this case the fractional decrease in length ranges from about four to ninety five percent being largest when an excessively high confidence based on a few observations is desired, the gain produced being larger than the sacrifice.

The range method of estimating confidence intervals is the

easiest to compute. When the underlying distribution is normal, the expected increase in interval length using the range is shown by Noether (1955) to be negligible for all practical purposes.

7.3 Monte Carlo Example

One way of investigating the robustness of the three confidence interval estimation methods, to departures from the normality assumptions, is to use Monte Carlo techniques. As an illustration of the type of results which may be obtained by this technique, the PURGE2 and MIX subroutines are used to generate large sequences of random numbers from various distributions for which the true means are known. These numbers are used to compute (95% normal theory) confidence intervals for sample sizes of five and ten by the three methods. The mean interval lengths are computed and since the true means are known, the confidence levels are also computed.

A summary of the results of these calculations is contained in Tables 15 thru 21. The first column in these tables specifies the total number N of numbers generated for the distribution. Several values of N are given in each table in order to indicate how the data is converging.

Table 14 gives the distributions used in Tables 15 thru 21 along with the moments of the distribution. Table 15, computed from a $N(0,1)$ distribution, is provided for comparison with the other tables.

The graphs of the distributions used in Tables 19 and 20 appear

as Figures 3 and 4 respectively. Table 21 is computed from a mixture of 40% χ_{10}^2 , 40% $N(8,10)$ and 20% uniform on $(8,10)$. The graph of this distribution is obtained from the MIX subroutine without smoothing and appears in Figure 14.

Table 14. Types of Curves Used in Tables 15 Thru 21

Table	Distribution	Shape	μ_1^i	μ_2	μ_3	μ_4
14	Normal	Bell	0.	1.000	0.	3.000
15	Type III (χ_{10}^2)	Bell	10.000	20.000	80.000	1680.000
16	Type I	Bell	0.	29.501	190.112	4361.120
17	Type I	J	0.051	4.266	-7.688	48.154
18	Type I	U	0.570	8.374	0.026	124.460
19	Type I	L	2.909	6.270	10.990	102.500
20	Mixture	Bell	9.000	12.867	44.000	992.840

Table 15. Confidence Interval Data (normal)

Nx10 ⁻³	Sample Size Five					
	s.s.d.		s.m.a.d.		range	
	c.l.	i.l.	c.l.	i.l.	c.l.	i.l.
17	0.949	2.317	0.952	2.403	0.951	2.357
18	0.948	2.317	0.952	2.401	0.949	2.357
19	0.947	2.313	0.952	2.397	0.948	2.353
20	0.947	2.317	0.952	2.401	0.949	2.356
Sample Size Ten						
17	0.944	1.382	0.947	1.423	0.943	1.404
18	0.942	1.382	0.946	1.422	0.942	1.404
19	0.941	1.381	0.945	1.420	0.941	1.403
20	0.942	1.382	0.946	1.422	0.942	1.405

Table 16. Confidence Interval Data (χ^2_{10})

Nx10 ⁻³	Sample Size Five					
	s.s.d.		s.m.a.d.		range	
	c.l.	i.l.	c.l.	i.l.	c.l.	i.l.
20	0.936	6.164	0.938	6.297	0.932	6.225
30	0.938	6.162	0.940	6.292	0.935	6.224
40	0.937	6.144	0.940	6.272	0.937	6.206
50	0.936	6.155	0.939	6.286	0.936	6.218

Table 17. Confidence Interval Data (Type I Bell)

Nx10 ⁻³	Sample Size Five					
	s.s.d.		s.m.a.d.		range	
	c.l.	i.l.	c.l.	i.l.	c.l.	i.l.
3	0.928	12.384	0.932	12.810	0.925	12.479
6	0.927	12.601	0.936	13.096	0.927	12.627
9	0.928	12.491	0.934	12.959	0.929	12.551
12	0.926	12.376	0.931	12.825	0.928	12.440

Table 18. Confidence Interval Data (Type I J)

Nx10 ⁻³	Sample Size Five					
	s.s.d.		s.m.a.d.		range	
	c.l.	i.l.	c.l.	i.l.	c.l.	i.l.
3	0.895	4.757	0.897	5.051	0.892	4.615
6	0.900	4.803	0.899	5.109	0.896	4.638
9	0.903	4.823	0.902	5.117	0.899	4.669
12	0.905	4.823	0.906	5.113	0.903	4.673

Table 19. Confidence Interval Data (Type I U)

Nx10 ⁻³	Sample Size Five					
	s.s.d.		s.m.a.d.		range	
	c.l.	i.l.	c.l.	i.l.	c.l.	i.l.
3	0.938	7.707	0.942	7.544	0.928	6.936
6	0.938	7.108	0.942	7.570	0.934	6.997
9	0.938	7.109	0.941	7.556	0.936	7.017
12	0.941	7.127	0.945	7.575	0.940	7.035

Table 20. Confidence Interval Data (Type I L)

Nx10 ⁻³	Sample Size Five					
	s.s.d.		s.m.a.d.		range	
	c.l.	i.l.	c.l.	i.l.	c.l.	i.l.
3	0.932	5.974	0.932	6.300	0.938	5.915
6	0.937	5.930	0.937	6.249	0.938	5.877
9	0.928	5.812	0.931	6.131	0.931	5.752
12	0.930	5.817	0.932	6.135	0.931	5.757

Table 21. Confidence Interval Data (Mixture Bell)

Nx10 ⁻³	Sample Size Five					
	s.s.d.		s.m.a.d.		range	
	c.l.	i.l.	c.l.	i.l.	c.l.	i.l.
17	0.964	8.057	0.969	8.198	0.963	8.251
18	0.963	8.067	0.968	8.209	0.963	8.258
19	0.962	8.037	0.967	8.117	0.961	8.231
20	0.963	8.024	0.967	8.164	0.962	8.220

Nx10 ⁻³	Sample Size Ten					
	s.s.d.		s.m.a.d.		range	
	c.l.	i.l.	c.l.	i.l.	c.l.	i.l.
17	0.954	4.876	0.961	4.750	0.953	5.170
18	0.956	4.881	0.962	4.752	0.953	5.179
19	0.957	4.866	0.963	4.735	0.955	5.165
20	0.956	4.858	0.962	4.729	0.955	5.159

7.4 Conclusions

The data in Tables 15 thru 21 indicate that none of the confidence interval estimation methods are greatly influenced by departures from normality.

The lowest confidence levels are about 90% and occur with the J shaped distribution used in Table 18. For this distribution, the confidence levels for each method do not appear to be significantly different. Here the shortest mean interval length is given by the range method being about 9% shorter than that of the sample mean absolute deviation and about 3% shorter than that of the sample standard deviation.

The only distribution with mean confidence levels greater than 95% is the mixture given in Table 21. For this distribution, the mean confidence level is about 96% for each method regardless of sample size. For samples of size ten, the sample mean absolute deviation gives the shortest interval length being about 8% shorter than that of the range and about 3% shorter than that of the sample standard deviation. For sample size five, the sample standard deviation gives the shortest mean interval length being about 2% shorter than that of the range and sample mean absolute deviation.

These results are by no means conclusive and the need for further study is indicated.

VIII. ACKNOWLEDGEMENTS

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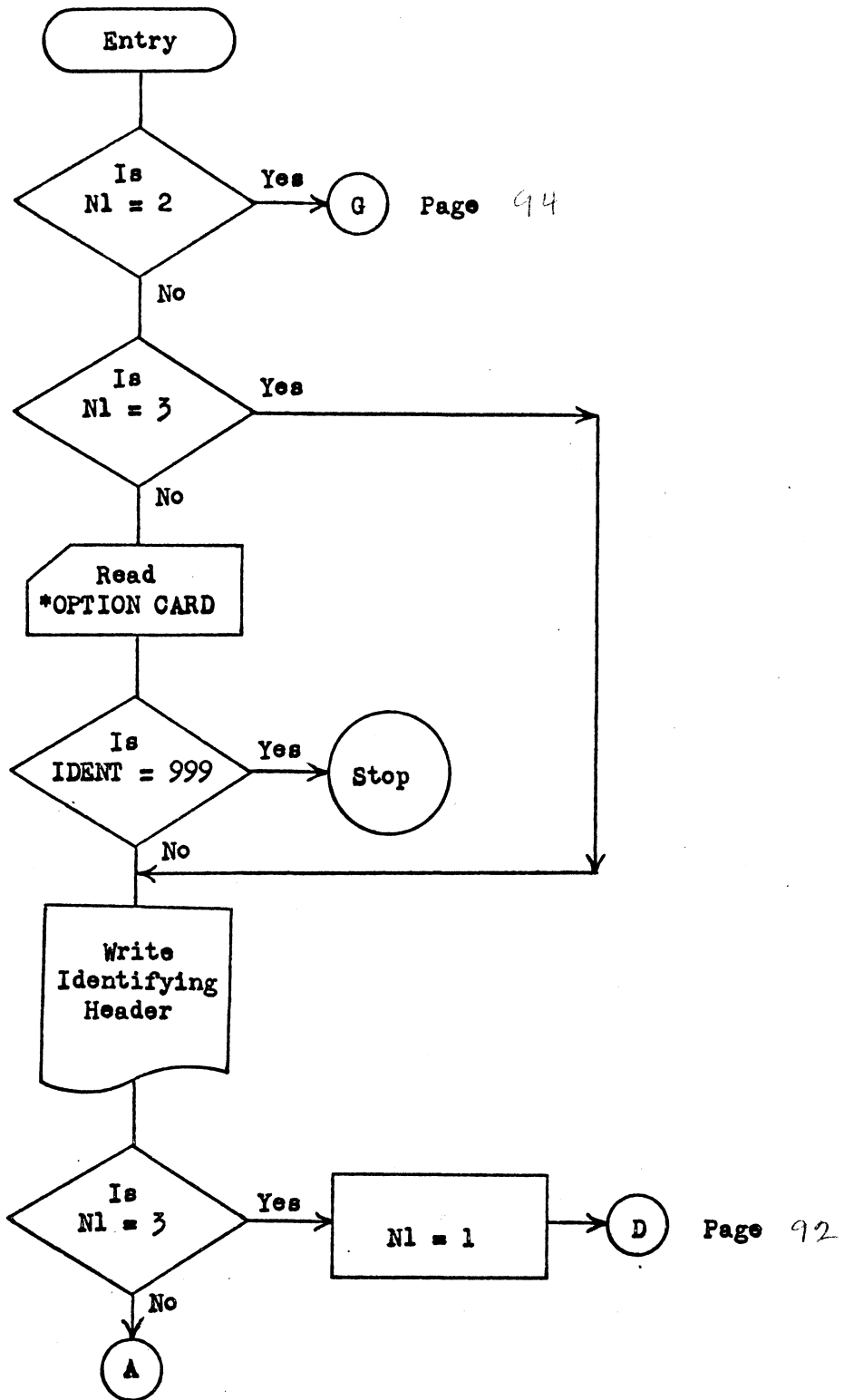
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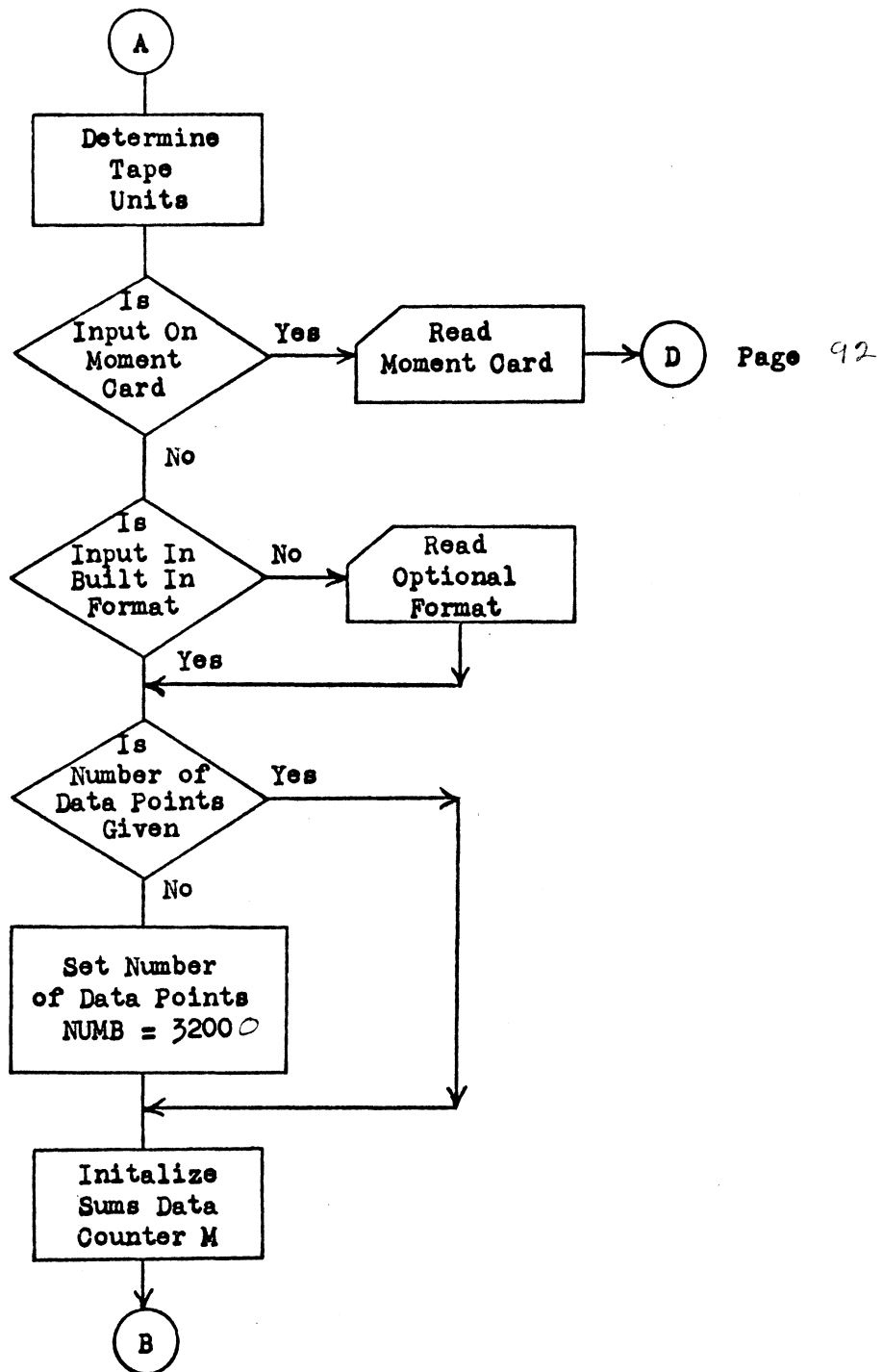
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XI. APPENDIX

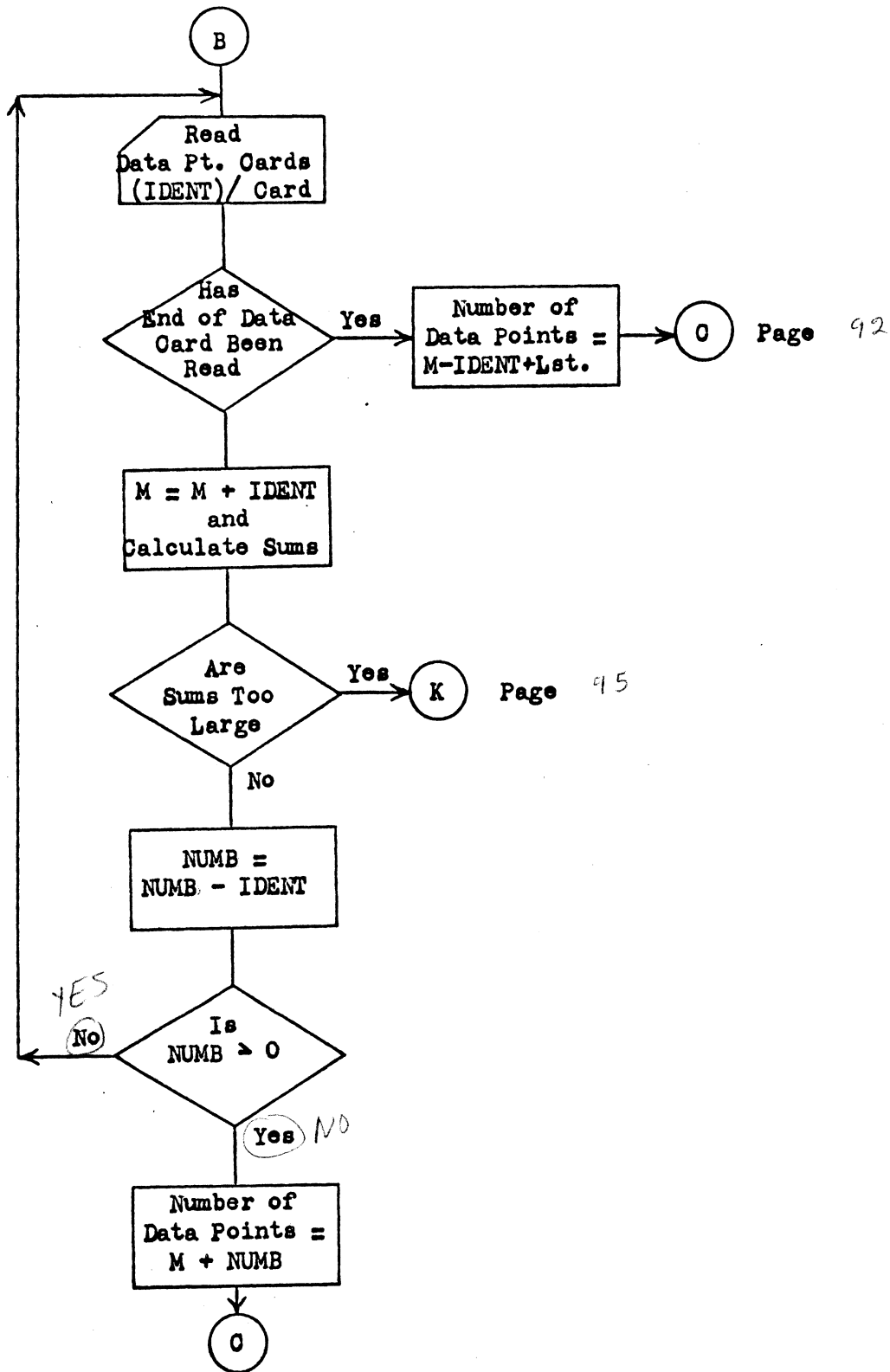


Flowchart For PURGE2

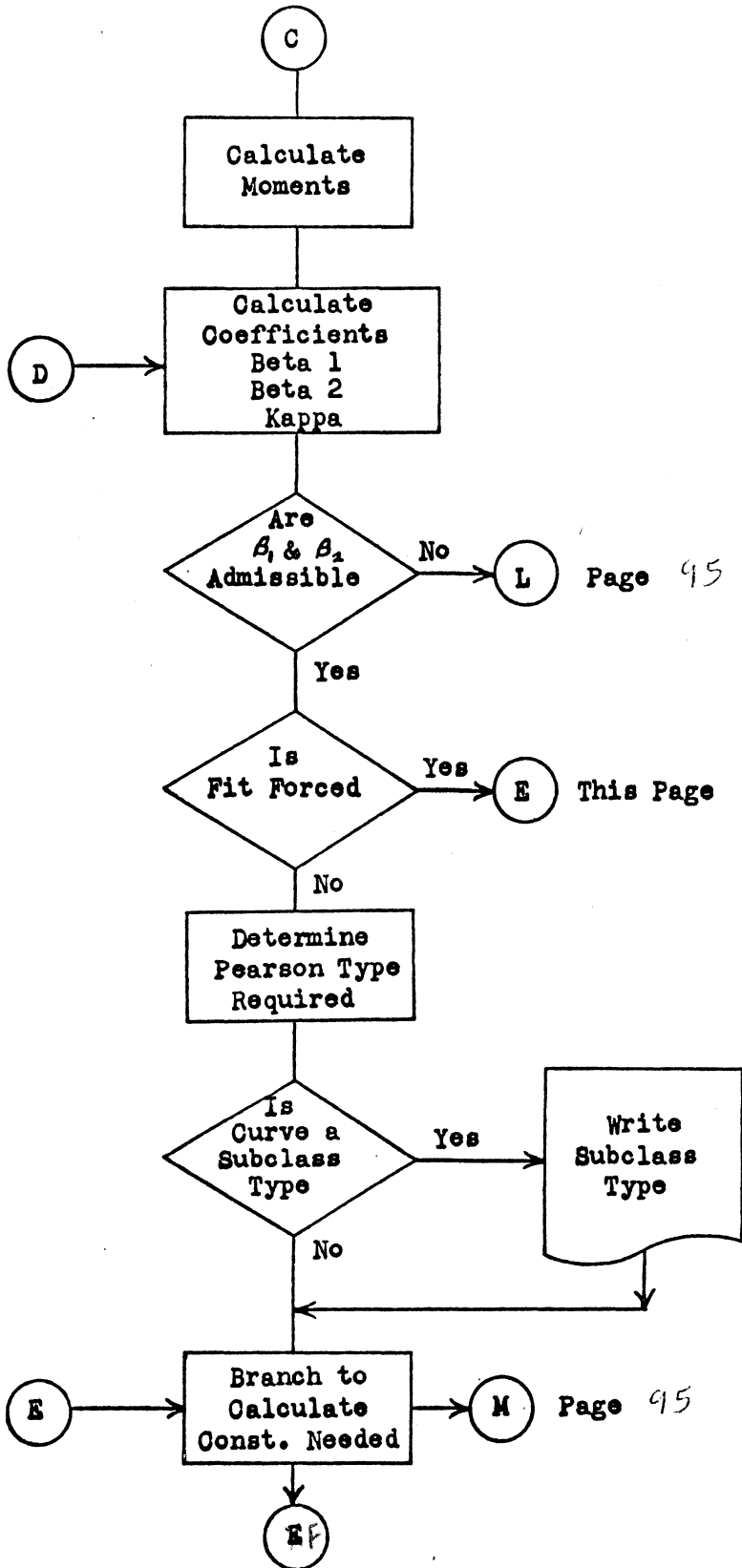


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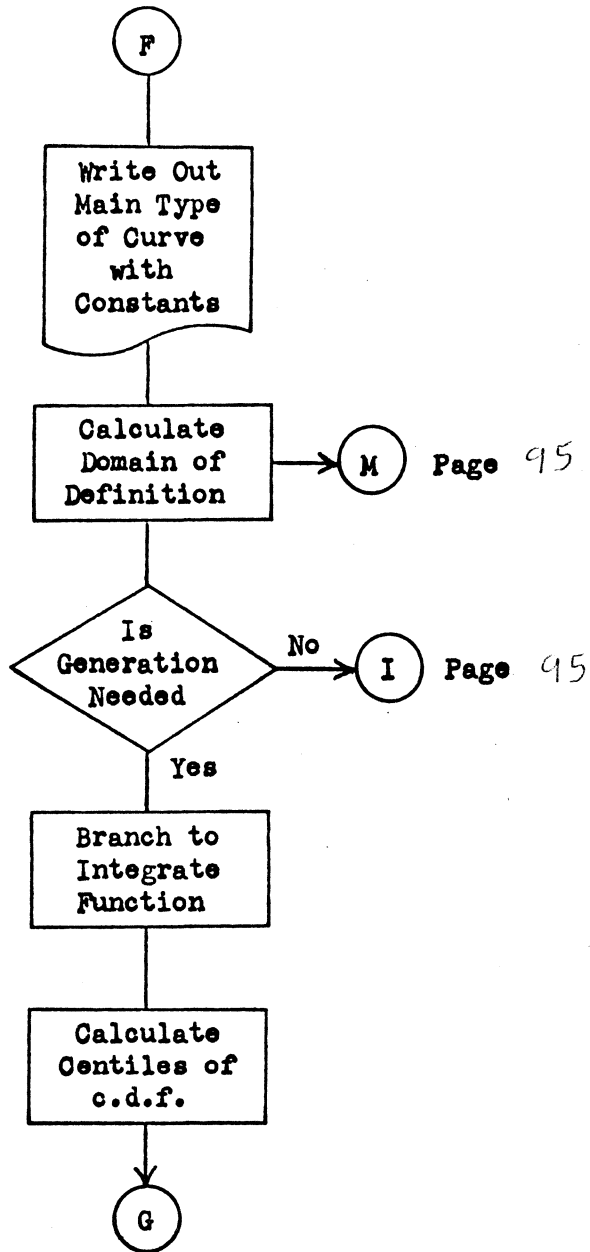
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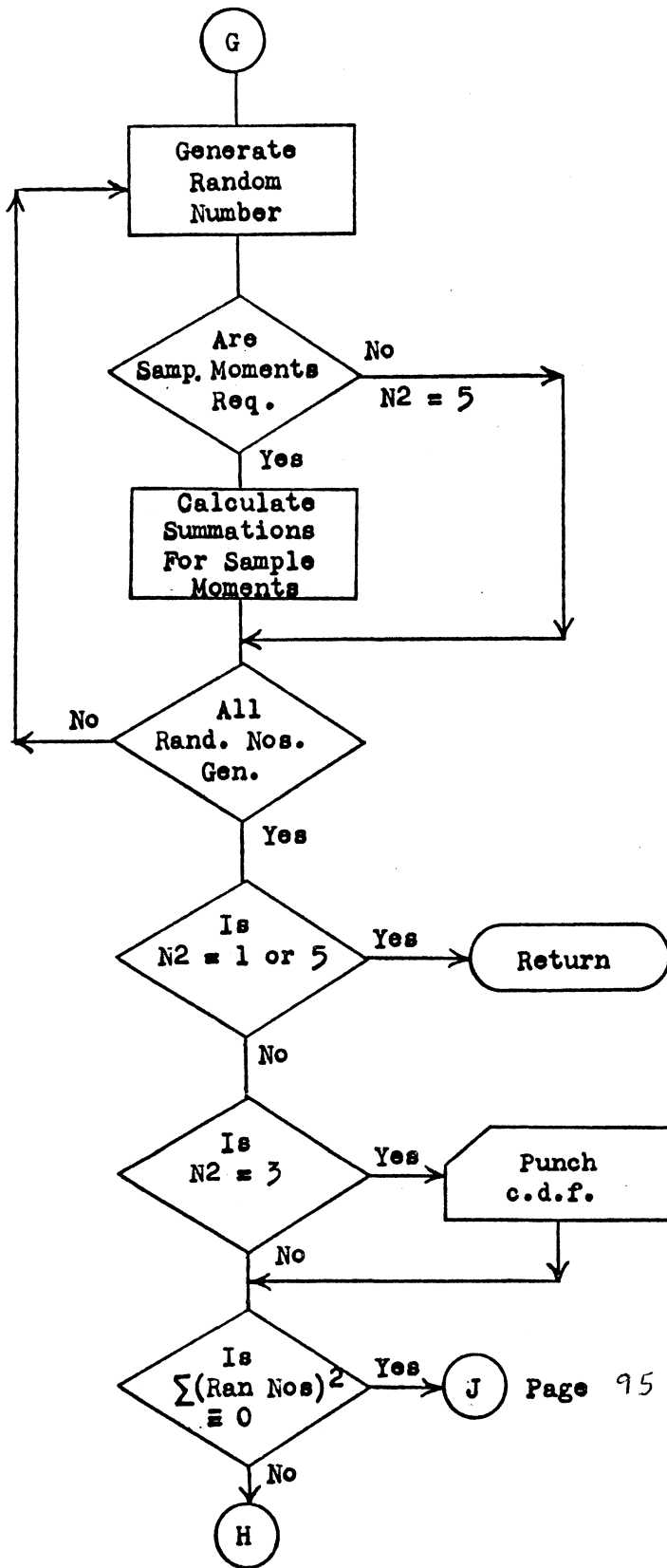
Flowchart For PURGE2, ctd.



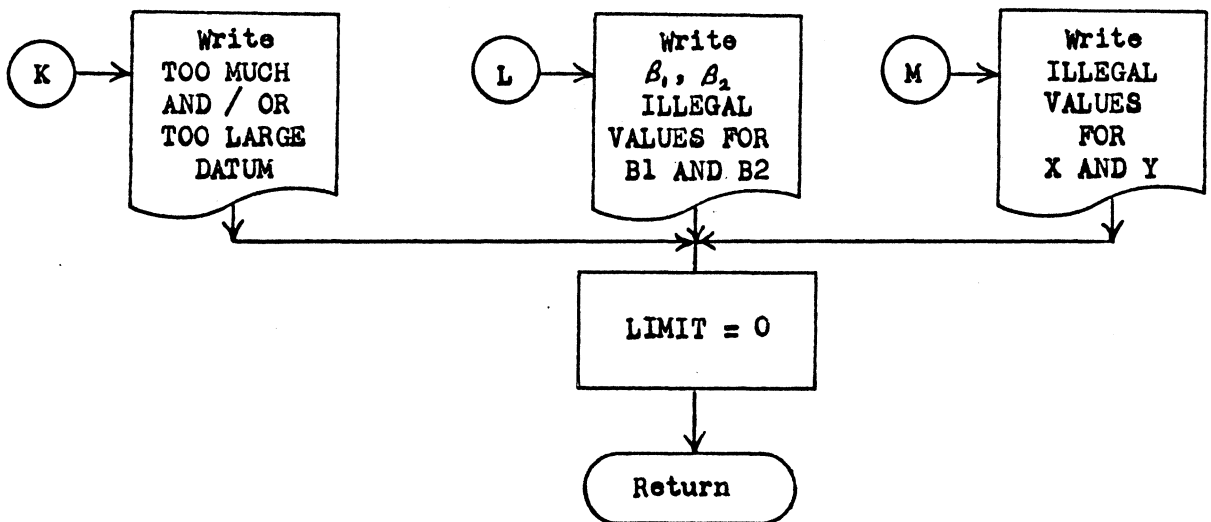
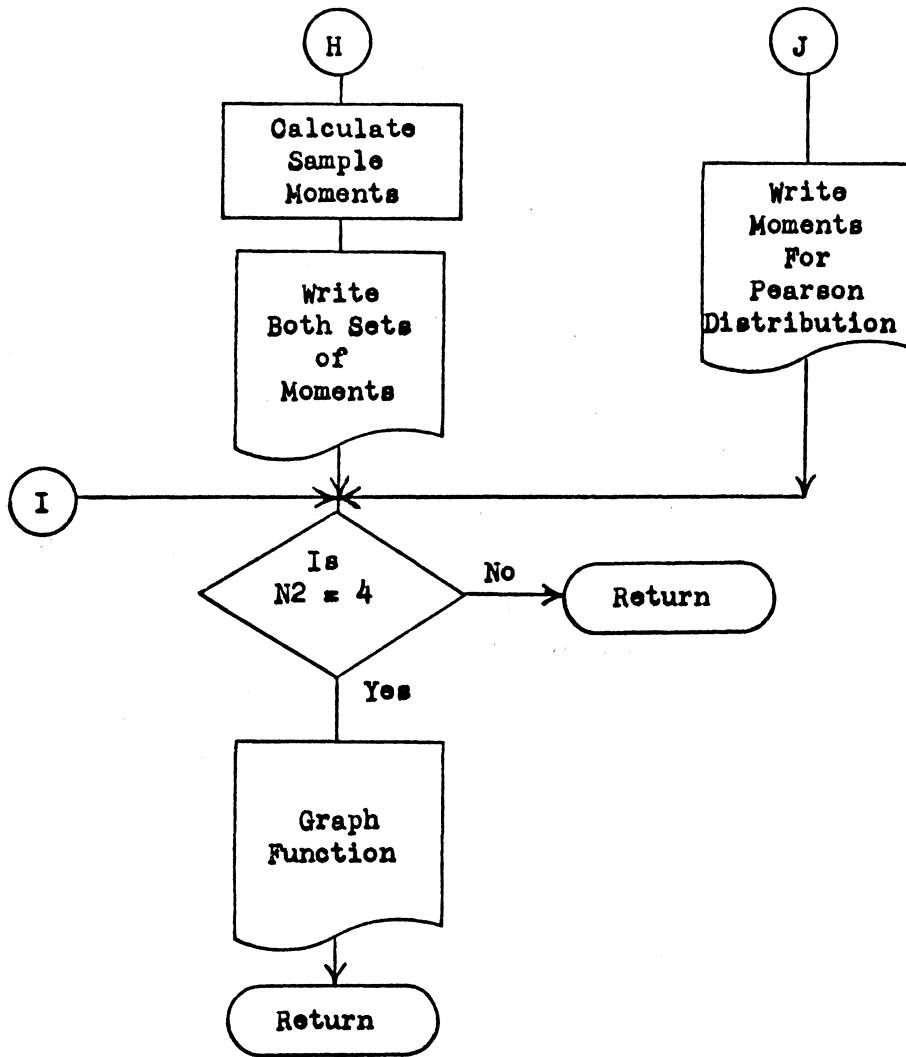
Flowchart For PURGE2, ctd.



Flowchart For PURGE2, ctd.



Flowchart For PURGE2, ctd.



Flowchart For PURGE2, ctd.

	1KU(93))		PURGE038
	DOUBLE PRECISION A,AN,X,Z,W		PURGE039
	IF(N1.EQ.2) GO TO 696		PURGE040
695	LT=0		PURGE041
	LIMIT=100		PURGE042
C			PURGE043
C			PURGE044
	NT1=0		PURGE045
C		CHANGE NEXT 2 CARDS FOR SPECIAL TAPE CONFIGURATI	PURGE046
	NINTP=5		PURGE047
	NOUTP=6		PURGE048
C			PURGE049
C			PURGE050
C			PURGE051
	L2=NINTP		PURGE052
	L3=NOUTP		PURGE053
9831	CALL OVERFL(J)		PURGE054
	IF(N1 .EQ. 3) GO TO 604		PURGE055
C			PURGE056
C		READ *CONTROL CARD	PURGE057
9030	READ (L2,1)IDENT,NUMB,LIMIT,NORM,ITT,NOUT		PURGE058
1	FORMAT (3X,I3,3X,I6,3X,I6,3X,I3,3X,I2,3X,I2)		PURGE059
	IF(IDENT - 999) 604,605,604		PURGE060
604	L2=NINTP		PURGE061
	L3=NOUTP		PURGE062
C			PURGE063
	WRITE (L3,9022)		PURGE064
9022	FORMAT (1H1, 92X,22HDISTRIBUTION GENERATOR)		PURGE065
	DO 600 I=1,2641		PURGE066
600	S(I)=0.		PURGE067
	IF(N1.NE.3) GO TO 2080		PURGE068
	N1=1		PURGE069
	GO TO 2081		PURGE070
C		DETERMINE OPTIONS	PURGE071
C		TAPES	PURGE072
2080	IF (ITT) 2,2,3		PURGE073
2	ITT=L2		PURGE074

3	IF (NOUT) 4,4,5		PURGE075
4	NOUT=L3		PURGE076
C		TYPE OF INPUT	PURGE077
5	IF (IDENT) 40,8,6		PURGE078
C		DATA POINT	PURGE079
6	READ (L2,7)(FM(I),I=1,12)		PURGE080
7	FORMAT (12A6)		PURGE081
	GO TO 10		PURGE082
C		BUILT IN FORMAT	PURGE083
8	CALL ATHRUZ(FM(1),6H(4X,4F)		PURGE084
	CALL ATHRUZ(FM(2),6H17.8,6)		PURGE085
	CALL ATHRUZ(FM(3),5HX,I2))		PURGE086
	IDENT=4		PURGE087
C		NUMBER OF DP CARDS GIVEN	PURGE088
C		OR CALCULATED	PURGE089
10	IF (NUMB) 11,11,12		PURGE090
11	NUMB=32000		PURGE091
12	M=0		PURGE092
C		INITIALIZE SUMS	PURGE093
	AN(1)=0.		PURGE094
	AN(2)=0.		PURGE095
	AN(3)=0.		PURGE096
	AN(4)=0.		PURGE097
C		READ DATA POINT CARDS	PURGE098
13	READ (ITT,FM)(X(I),I=1,IDENT),LST		PURGE099
	IF (LST) 14,14,20		PURGE100
14	M=M+IDENT		PURGE101
C		CALCULATE SUMS	PURGE102
15	DO 17 I=1,IDENT		PURGE103
	AN(1)=AN(1)+X(I)		PURGE104
	Z=X(I)*X(I)		PURGE105
	AN(2)=AN(2)+Z		PURGE106
	Z=Z*X(I)		PURGE107
	AN(3)=AN(3)+Z		PURGE108
17	AN(4)=AN(4)+X(I)*Z		PURGE109
	CALL OVERFL(J3K)		PURGE110
	GO TO (780,16,16),J3K		PURGE111

780	LIMIT=0		PURGE112
16	NUMB=NUMB-IDENT		PURGE113
C		DETERMINE OF DP CARDS	PURGE114
	IF (NUMB) 25,25,13		PURGE115
20	M=M-IDENT+LST		PURGE116
	GO TO 27		PURGE117
25	M=M+NUMB		PURGE118
C		HOW MANY DP	PURGE119
27	FN=M		PURGE120
	IF(LIMIT.EQ.0) GO TO 910		PURGE121
C		FORM MOMENTS	PURGE122
	DO 30 K=1,4		PURGE123
30	A(K)=AN(K)/FN		PURGE124
	Z=A(1)*A(1)		PURGE125
	CM2=A(2)-Z		PURGE126
	W=A(1)*A(2)		PURGE127
	Z=Z*A(1)		PURGE128
	CM3=A(3)-3.*W +2.*Z		PURGE129
	CM4=A(4)-4.*A(1)*A(3)+6.*A(1)*W -3.*A(1)*Z		PURGE130
	AVE=A(1)		PURGE131
	RCM2=SQRT(CM2)		PURGE132
C			PURGE133
C		CALCULATE COEFF FOR PEARSON	PURGE134
C			PURGE135
35	TP=CM2*CM2		PURGE136
	BETA1=CM3**2/(CM2*TP)		PURGE137
	BETA2=CM4/TP		PURGE138
C	DETERMINE IF BETA1 AND BETA2 ADMISSIBLE		PURGE139
	IF(((BETA1-BETA2+1.)/(-1.414213562).LT.0.).OR.(BETA1.LT.0.).OR.		PURGE140
	1((15.*BETA1-8.*BETA2+36.)/(-17.).GE.0.)) GO TO 750		PURGE141
	DOP=0.		PURGE142
	SK1=BETA1*(BETA2+3.)**2		PURGE143
	SK2=4.*(4.*BETA2-3.*BETA1)*(2.*BETA2-3.*BETA1-6.)		PURGE144
	IF (SK1) 351,621,351		PURGE145
351	IF (SK2) 352,353,352		PURGE146
352	SKAPPA=SK1/SK2		PURGE147
	GO TO 45		PURGE148

621	SKAPPA=0.		PURGE149
	GO TO 45		PURGE150
353	SKAPPA=(10.**10)**10		PURGE151
	IF (BETA1-4.) 8008,8007,8008		PURGE152
8007	WRITE (L3,8006)		PURGE153
8006	FORMAT(1H ,35X,17HSUBCLASS TYPE TEN)		PURGE154
	DOP=1.		PURGE155
	GO TO 45		PURGE156
8008	WRITE (L3,8009)		PURGE157
8009	FORMAT(1H ,35X,19HSUBCLASS TYPE THREE)		PURGE158
	DOP=1.		PURGE159
	GO TO 45		PURGE160
C		READ MOMENTS CARD IF NECCESAR	PURGE161
40	READ (ITT,9023) AVE,CM2,CM3,CM4		PURGE162
9023	FORMAT (4X,4F17.8)		PURGE163
2081	RCM2=SQRT(CM2)		PURGE164
	GO TO 35		PURGE165
C		DETERMINE MAIN TYPE	PURGE166
C		OR FORCE FIT	PURGE167
45	IF (NORM-1) 451,50,452		PURGE168
452	IF (NORM-6) 71,111,90		PURGE169
451	IF (DOP) 453,453,9400		PURGE170
453	IF (SKAPPA) 50,8001,8002		PURGE171
8001	IF (BETA2-3.) 8004,90,8003		PURGE172
8002	IF (SKAPPA-1.) 71,8005,111		PURGE173
8004	WRITE (L3,8010)		PURGE174
8010	FORMAT(1H ,35X,17HSUBCLASS TYPE TWO)		PURGE175
	GO TO 50		PURGE176
8003	WRITE (L3,8011)		PURGE177
8011	FORMAT(1H ,35X,19HSUBCLASS TYPE SEVEN)		PURGE178
	GO TO 71		PURGE179
8005	WRITE (L3,8012)		PURGE180
8012	FORMAT(1H ,35X,18HSUBCLASS TYPE FIVE)		PURGE181
	GO TO 111		PURGE182
C			PURGE183
C		TYPE ONE CONSTANTS	PURGE184
C			PURGE185

50	WRITE	(L3,51)	PURGE186
51	FORMAT(1H ,30X,22HPEARSON CURVE TYPE ONE)		PURGE187
511	R=6.*(BETA2-BETA1-1.)/(6.+3.*BETA1-2.*BETA2)		PURGE188
	TP=	R*(R+2.)*SQRTF(BETA1/(BETA1*(R+2.)**2+16.*(R+1.)))	PURGE189
	RP=.5*(R-2.+TP)		PURGE190
	RM=.5*(R-2.-TP)		PURGE191
53	IF (CM3) 57,56,56		PURGE192
56	D2=RP		PURGE193
	D1=RM		PURGE194
	GO TO 58		PURGE195
57	D1=RP		PURGE196
	D2=RM		PURGE197
58	SCOTT=.5*RCM2	*SQRTF(BETA1*(R+2.)**2+16.*(R+1.))	PURGE198
	B2=SCOTT*(D2+1.)/(D2+D1+2.)		PURGE199
	B1=SCOTT-B2		PURGE200
	IF((D1+1.)*(D2+1.)) 903,903,582		PURGE201
582	IF (B1+B2) 583,906,583		PURGE202
583	Y0=SIGNF(1.0,B1+B2)*EXPF(D1*LOGF(D1+1.)-LOGF(ABSF(B1+B2))-LGAMF(D1		PURGE203
	+2+1.)+D2*LOGF(D2+1.)-LGAMF(D2+1.)+LGAMF(D1+D2+2.)-(D1+D2)*LOGF(D1+D		PURGE204
	32+2.))		PURGE205
585	WRITE	(L3,581)D1,D2,B1,B2,Y0	PURGE206
581	FORMAT (4HOM1=,1PE12.5,4H M2=,1PE12.5,4H A1=,1PE12.5,4H A2=,1PE12.		PURGE207
	25,4H YE=,1PE12.5)		PURGE208
	V1=B1		PURGE209
	V2=B2		PURGE210
	V3=D1		PURGE211
	V4=D2		PURGE212
C		JAB IS FOR INTEGRATION BRANCH	PURGE213
	JAB=1		PURGE214
	IF(B2) 60,906,63		PURGE215
60	IF (B1) 61,61,906		PURGE216
C		RANGES	PURGE217
61	H=(-B1-B2)/5120.		PURGE218
	UPPER=-B1		PURGE219
	EL=B2		PURGE220
	GO TO 145		PURGE221
63	IF (B1) 906,64,64		PURGE222

64	H=(B2+B1)/5120. UPPER=B2 EL=-B1 GO TO 145	PURGE223 PURGE224 PURGE225 PURGE226 PURGE227 PURGE228 PURGE229
C C C	TYPE FOUR CONSTANTS	PURGE230 PURGE231 PURGE232 PURGE233 PURGE234 PURGE235 PURGE236 PURGE237 PURGE238 PURGE239 PURGE240 PURGE241 PURGE242 PURGE243 PURGE244 PURGE245 PURGE246 PURGE247 PURGE248 PURGE249 PURGE250 PURGE251 PURGE252 PURGE253 PURGE254 PURGE255 PURGE256 PURGE257 PURGE258 PURGE259
71	WRITE (L3,72)	
72	FORMAT(1H ,30X,23HPEARSON CURVE TYPE FOUR)	
73	R=6.*(BETA2-BETA1-1.)/(2.*BETA2-3.*BETA1-6.)	
74	D=.5*(R+2.)	
75	V=R*(R-2.)*SQRTF(BETA1)/SQRTF(16.*(R-1.)-BETA1*(R-2.)**2)	
76	B=SQRTF(CM2/16.)*SQRTF(16.*(R-1.)-BETA1*(R-2.)**2) IF (CM3)77,783,783	
783	V=-V	
77	PHI=ATANF(V/R)	
78	TOP= ((COSF(PHI))**2/(3.*R)-1.)/(12.*R)-PHI*V Y0=LOGF(0.3989423)-LOGF(B)+.5*LOGF(R)+TOP-(R+1.)*LOGF(COSF(PHI)) IF (Y0-88.9) 782,782,784	
782	Y1=EXPF(Y0) GO TO 785	
784	Y1=.99999999E 38	
785	WRITE (L3,781)R,D,V,B,Y1	
781	FORMAT (3HOR=,1PE12.5,4H M=,1PE12.5,4H V=,1PE12.5,3H A=,1PE12.5, 24H Y0=,1PE12.5) JAB=2 H=RCM2 /512. UPPER=5.* RCM2 EL=-UPPER V1=B V2=V V3=R V4=D GO TO 145	
C C C	NORMAL CURVE CONSTANTS	

90	WRITE	(L3,91)	PURGE260
91	FORMAT(1H ,30X,29H	THIS IS A NORMAL DISTRIBUTION)	PURGE261
92	C=CM2*2.		PURGE262
	Y0=1./SQRTF(6.2831853*CM2)		PURGE263
	WRITE	(L3,1101)C,Y0	PURGE264
1101	FORMAT (3HOC=,1PE12.5,4H Y0=,1PE12.5)		PURGE265
	JAB=3		PURGE266
	H=RCM2 /512.		PURGE267
	UPPER=5.*RCM2		PURGE268
	EL=-UPPER		PURGE269
	V1=C		PURGE270
	GO TO 145		PURGE271
C			PURGE272
C		TYPE SIX CONSTANTS	PURGE273
C			PURGE274
111	WRITE	(L3,112)	PURGE275
112	FORMAT(1H ,30X,22H	PEARSON CURVE TYPE SIX)	PURGE276
113	R=6.*(BETA2-BETA1-1.)/(6.+3.*BETA1-2.*BETA2)		PURGE277
	CAT=.5*RCM2 *SQRTF(BETA1*(R+2.)**2+16.*(R+1.))		PURGE278
	IF (CM3) 9836,9837,9837		PURGE279
9836	CAT=-CAT		PURGE280
9837	TERM=R*(R+2.)/2.*SQRTF(BETA1/(BETA1*(R+2.)**2+16.*(R+1.)))		PURGE281
	D2=(R-2.)/2.+TERM		PURGE282
	D1=-((R-2.)/2.-TERM)		PURGE283
	TP= ((D1-1.)-(D2+1.))		PURGE284
	B1=CAT*(D1-1.)/TP		PURGE285
	B2=CAT*(D2+1.)/TP		PURGE286
	CAC1=1.		PURGE287
	Y0=(D2*LOGF(D2+1.)-LGAMF(D2+1.)-LOGF(CAT)+(D1-D2)*LOGF(D1-D2-2.)-D		PURGE288
	21*LOGF(D1-1.)+LGAMF(D1)-LGAMF(D1-D2-1.))+LOGF(CAC1)		PURGE289
	Y1=EXPF(Y0)		PURGE290
	WRITE	(L3,1134)D2,D1,B1,B2,Y1	PURGE291
1134	FORMAT (4HQ2=,1PE12.5,4H Q1=,1PE12.5,4H A1=,1PE12.5,4H A2=,1PE12.		PURGE292
	25,4H YE=,1PE12.5)		PURGE293
	JAB=4		PURGE294
	V1=B1		PURGE295
	V2=B2		PURGE296

```

V3=D1
V4=D2
IF (B2 ) 115,906,120
115 H=(-B2+5.*RCM2 )/5120.
    UPPER=-B2
    EL=-5.*RCM2
    GO TO 145
120 UPPER=5.*RCM2
    H=(B2+UPPER )/5120.
    EL=-B2
    GO TO 145

```

C
C
C

TYPE THREE CONSTANTS

```

9400 G=2.*CM2/CM3
    P=4./BETA1-1.
    A1=(P+1.)/G
    Y0=G*(P+1.)*P/EXPF(P+1.+LGAMF(P+1.))
    Y0=ABSF(Y0)
    WRITE (L3,9401)G,P,A1,Y0
9401 FORMAT (3H0G=,1PE12.5,3H P=,1PE12.5,3H A=,1PE12.5,4H YE=,1PE12.5)
    JAB=5
    V1=G
    V2=P
    V3=A1
    IF (A1) 9402,9403,9403
9402 H=(-A1+5.*RCM2 )/5120.
    UPPER=-A1
    EL=-5.*RCM2
    GO TO 145
9403 UPPER=5.*RCM2
    H=(A1+UPPER )/5120.
    EL = -A1

```

C
C
C

INITIALIZE OUTPUT SUMS
GENERATION
BRANCH TO INTEGRATE

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950 FORMAT(1H )

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- PURGE297
- PURGE298
- PURGE299
- PURGE300
- PURGE301
- PURGE302
- PURGE303
- PURGE304
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- PURGE327
- PURGE328
- PURGE329
- PURGE330
- PURGE331
- PURGE332
- PURGE333

```

145  V0=Y0
      V6=EL
      V7=UPPER
951  DO 146 KK=1,4
146  FAN(KK)=0.
      IF (LIMIT) 148,148,147
147  S(1)=0.
153  GO TO (200,250,300,350,460),JAB

```

```

C
C
C

```

TYPE ONE INTEG

```

200  IF (D1) 2054,2055,2055
2055 IF (D2) 2056,2057,2057
2057 EXVAL=EL
      ADD1=EL+H
      TP= H+H
      XVAL=EL+TP
      I=2
205  SKUNK(1)=PEARIF(Y0,B1,B2,D1,D2,EXVAL)
2051 SKUNK(2)=PEARIF(Y0,B1,B2,D1,D2,ADD1)
2052 SKUNK(3)=PEARIF(Y0,B1,B2,D1,D2,XVAL)
2053 S(I)=S(I-1)+SKUNK(1)+4.*SKUNK(2)+SKUNK(3)
      IF (XVAL+TP-UPPER)210,210,385
210  EXVAL=XVAL
      ADD1=XVAL+H
      XVAL=XVAL+TP
      I=I+1
      GO TO 205

```

```

C
C

```

TYPE ONE L SHAPE

```

2054 IF (D2) 7001,3001,3001
3001 H=(UPPER-EL)/5121.
      EL=EL+H
      EXVAL=EL
      ADD1=EL+H
      TP= H+H
      XVAL=EL+TP

```

```

PURGE334
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PURGE369
PURGE370

```

```

S(2)=0.
I=3
3002 SKUNK(1)=PEARIF(Y0,B1,B2,D1,D2,EXVAL)
      SKUNK(2)=PEARIF(Y0,B1,B2,D1,D2,ADD1)
      SKUNK(3)=PEARIF(Y0,B1,B2,D1,D2,XVAL)
      S(I)=S(I-1)+SKUNK(1)+4.*SKUNK(2)+SKUNK(3)
      IF (XVAL+TP-UPPER)3003,3003,3004
3003 EXVAL=XVAL
      ADD1=XVAL+H
      XVAL=XVAL+TP
      I=I+1
      GO TO 3002
3004 S(2)=3./H-S(1)
4005 N=I
      DO 4006 I=3,N
4006 S(I)=S(I)+S(2)
      I=N
      GO TO 385

```

C
C

TYPE ONE U SHAPE

```

7001 H=(UPPER-EL)/5122.
      EL=EL+H
      UPPER=UPPER-H
      EXVAL=EL
      ADD1=EL+H
      TP= H+H
      XVAL=EL+TP
      I=2
7002 SKUNK(1)=PEARIF(Y0,B1,B2,D1,D2,EXVAL)
      SKUNK(2)=PEARIF(Y0,B1,B2,D1,D2,ADD1)
      SKUNK(3)=PEARIF(Y0,B1,B2,D1,D2,XVAL)
      S(I)=S(I-1)+SKUNK(1)+4.*SKUNK(2)+SKUNK(3)
      IF (XVAL+TP-UPPER)7003,7003,385
7003 EXVAL=XVAL
      ADD1=XVAL+H
      XVAL=XVAL+TP
      I=I+1

```

```

PURGE371
PURGE372
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PURGE405
PURGE406
PURGE407

```

	GO TO 7002		PURGE408
C			PURGE409
C		TYPE ONE J SHAPE	PURGE410
	2056 H=(UPPER-EL)/5121.		PURGE411
	UPPER=UPPER-H		PURGE412
	EXVAL=EL		PURGE413
	ADD1=EL+H		PURGE414
	TP= H+H		PURGE415
	XVAL=EL+TP		PURGE416
	I=2		PURGE417
	4002 SKUNK(1)=PEARIF(YO,B1,B2,D1,D2,EXVAL)		PURGE418
	SKUNK(2)=PEARIF(YO,B1,B2,D1,D2,ADD1)		PURGE419
	SKUNK(3)=PEARIF(YO,B1,B2,D1,D2,XVAL)		PURGE420
	S(I)=S(I-1)+SKUNK(1)+4.*SKUNK(2)+SKUNK(3)		PURGE421
	IF (XVAL+TP-UPPER)4003,4003,385		PURGE422
	4003 EXVAL=XVAL		PURGE423
	ADD1=XVAL+H		PURGE424
	XVAL=XVAL+2.*H		PURGE425
	I=I+1		PURGE426
	GO TO 4002		PURGE427
C			PURGE428
C		TYPE FOUR INTEG	PURGE429
	250 EXVAL=EL		PURGE430
	ADD1=EL+H		PURGE431
	TP= H+H		PURGE432
	XVAL=EL+TP		PURGE433
	I=2		PURGE434
	255 SKUNK(1)=PEARIV (YO,B,V,R,D,EXVAL)		PURGE435
	SKUNK(2)=PEARIV (YO,B,V,R,D,ADD1)		PURGE436
	SKUNK(3)=PEARIV (YO,B,V,R,D,XVAL)		PURGE437
	S(I)=S(I-1)+SKUNK(1)+4.*SKUNK(2)+SKUNK(3)		PURGE438
	IF (XVAL-UPPER) 260,385,385		PURGE439
	260 EXVAL=XVAL		PURGE440
	ADD1=XVAL+H		PURGE441
	XVAL=XVAL+TP		PURGE442
	I=I+1		PURGE443
	GO TO 255		PURGE444

C
C

NORMAL INTEG

300 TP= H+H
EXVAL=EL-TP
ADD1=EL-H
XVAL=EL
I=2
305 SKUNK(1)=NORMAL (Y0,C,EXVAL)
SKUNK(2)=NORMAL (Y0,C,ADD1)
SKUNK(3)=NORMAL (Y0,C,XVAL)
S(I)=S(I-1)+SKUNK(1)+4.*SKUNK(2)+SKUNK(3)
IF (XVAL-UPPER) 310,385,385
310 EXVAL=XVAL
ADD1=XVAL+H
XVAL=XVAL+TP
I=I+1
GO TO 305

C
C

TYPE SIX INTRG

350 EXVAL=EL
ADD1=EL+H
TP= H+H
XVAL=EL+TP
I=2
3551 SKUNK(1)=0
GO TO 3553
3552 SKUNK(1)=PEARVI (Y0,B1,B2,D1,D2,EXVAL)
3553 SKUNK(2)=PEARVI (Y0,B1,B2,D1,D2,ADD1)
SKUNK(3)=PEARVI (Y0,B1,B2,D1,D2,XVAL)
3559 S(I)=S(I-1)+SKUNK(1)+4.*SKUNK(2)+SKUNK(3)
IF (XVAL-UPPER) 360,385,385
360 EXVAL=XVAL
ADD1=XVAL+H
XVAL=XVAL+TP
I=I+1
GO TO 3552

C

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PURGE481

```

C
460 EXVAL=EL
    ADD1=EL+H
    TP= H+H
    XVAL=EL+TP
    I=2
    SKUNK(1)=0
    GO TO 462
461 SKUNK(1)=PERIII (YO,G,P,A1,EXVAL)
462 SKUNK(2)=PERIII (YO,G,P,A1,ADD1)
    SKUNK(3)=PERIII (YO,G,P,A1,XVAL)
    S(I)=S(I-1)+SKUNK(1)+4.*SKUNK(2)+SKUNK(3)
    IF (XVAL-UPPER) 463,385,385
463 EXVAL=XVAL
    ADD1=XVAL+H
    XVAL=XVAL+TP
    I=I+1
    GO TO 461
385 A2B=H/3.
682 N=I+1
678 DO 3851 I=1,N
3851 S(I)=S(I)*A2B
    S(N+1)=1.

```

TYPE THREE INTEG

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```

C
C
9301 KU(1)=1
C
    A1=0.
    I=1
    DO 675 J=2,100
    A1=A1+.01
    M=I
    DO 676 I=M,N
    IF(S(I)-A1)676,675,675
676 CONTINUE
675 KU(J)=I
    KU(101)=N

```

RANDOM UNIT CALCULATION

```

C
CALL OVERFL(J3K)
696 DO 393 K=1,LIMIT
    RND=RDM(1.0)
    NR=INT(100.*RND)+1
    671 M=KU(NR)
        DO 387 I=M,N
            IF(S(I)-RND) 387,390,388
387 CONTINUE
388 BUT=FLOAT(I+I-2)-2.*(S(I)-RND)/(S(I)-S(I-1))
C
    GO TO 391
390 BUT=I+I-2
391 TOM(K)=EL+BUT*H+AVE
    IF(N2.EQ.5) GO TO 393
683 DO 685 KK=1,4
685 FAN(KK)=FAN(KK)+TOM(K)**KK
393 CONTINUE
C
    LT=LT+LIMIT
    GO TO (952,400,953,400,952),N2
952 RETURN
953 WRITE(7)N,KU,KT,EL,H,AVE,CM2,CM3,CM4
    WRITE(7) (S(I),I=1,N)
C
    CALC OUTPUT MOMENTS
400 IF(FAN(2).EQ.0.) GO TO 148
    TP=FLOAT(LT)
    DO 405 KK=1,4
405 FA(KK)=FAN(KK)/TP
    FCM2 =FA(2)-FA(1)**2
    FCM3 =FA(3)-3.*FA(1)*FA(2)+2.*FA(1)**3
    FCM4 =FA(4)-4.*FA(1)*FA(3)+6.*FA(1)**2*FA(2)-3.*FA(1)**4
    FBETA1=FCM3**2/FCM2**3
    FBETA2=FCM4/FCM2**2
    FKAPPA=FBETA1*(FBETA2+3.)**2/(4.*(4.*FBETA2-3.*FBETA1)*
2      (2.*FBETA2-3.*FBETA1-6.))
    CALL OVERFL(J3K)

```

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```

	IF(J3K.EQ.1) WRITE(6,922)	PURGE556
	922 FORMAT(6H OVRFL)	PURGE557
C		PURGE558
	WRITE BOTH SETS OF MOMENTS	PURGE559
	WRITE (L3,410) LT	PURGE560
410	FORMAT(1H0,27X,32HMOMENTS FROM ORIGINAL DATA,6X,	PURGE561
	219HFROM GENERATED DATA,6H N=,I6)	PURGE562
407	WRITE(L3,411)AVE,FA(1),CM2,FCM2,CM3,FCM3,CM4,FCM4,	PURGE563
2	BETA1,FBETA1,BETA2,FBETA2,SKAPPA,FKAPPA	PURGE564
411	FORMAT (35X,4HMEAN,3X,F18.8,4X,F18.8 /31X,8HVARIANCE,3X,F18.8,4X,	PURGE565
2	F18.8 /34X,5HMU(3),3X,F18.8,4X,F18.8 /34X,5HMU(4),	PURGE566
3	3X,F18.8,4X,F18.8 /33X,6HBETA 1,3X,F18.8,4X,F18.8/	PURGE567
4	33X,6HBETA 2,3X,F18.8,4X,F18.8 /34X,5HKAPPA,3X,	PURGE568
5	F18.8,4X,F18.8)	PURGE569
C		PURGE570
C		PURGE571
C		PURGE572
C		PURGE573
681	IF(N2.EQ.4) GO TO 680	PURGE574
	412 RETURN	PURGE575
C		PURGE576
C		PURGE577
	NO GENERATIN WRITE OUT	PURGE578
148	WRITE (L3,149)	PURGE579
149	FORMAT(1H0,51X,17HMOMENTS FROM DATA)	PURGE580
	WRITE (L3,150)AVE ,CM2,CM3,CM4,BETA1,BETA2,SKAPPA	PURGE581
150	FORMAT (54X,4HMEAN,4X,F18.8 /50X,8HVARIANCE,4X,F18.8 /53X,5HMU(3)	PURGE582
2	,4X,F18.8 /53X,5HMU(4),4X,F18.8 /52X,6HBETA 1,4X,F18.8 /52X,6HB	PURGE583
	BETA 2,4X,F18.8 /53X,5HKAPPA,4X,F18.8)	PURGE584
	IF(N2.EQ.4) GO TO 680	PURGE585
	RETURN	PURGE586
C		PURGE587
	GRAPH ROUTINE	PURGE588
680	WRITE(L3,950)	PURGE589
	DO 80 I=1,100	PURGE590
80	CALL ATHRUZ(O(I),1H)	PURGE591
	DO 81 I=1,5	PURGE592
81	SID(I)=0.	
	BOX=(V7-V6)/99.	
	Q=V6+BOX	

```

      PIP=0.
      SMAX=0.
      SMIN=(10.**10)**10
      DO 82 I=2,99
      GO TO (83,84,85,86,87),JAB
83  VAL(I)=PEARIF(V0,V1,V2,V3,V4,Q)
      GO TO 88
84  VAL(I)=PEARIV(V0,V1,V2,V3,V4,Q)
      GO TO 88
85  VAL(I)=NORMAL(V0,V1,Q)
      GO TO 88
86  VAL(I)=PEARVI(V0,V1,V2,V3,V4,Q)
      GO TO 88
87  VAL(I)=PERIII(V0,V1,V2,V3,Q)
88  BOT(I)=Q+AVE
      Q=Q+BOX
      IF(VAL(I)-SMAX) 93,93,89
89  SMAX=VAL(I)
93  IF(VAL(I)-SMIN) 94,82,82
94  SMIN=VAL(I)
82  CONTINUE
      N=0
      DO 95 K=1,5
      E=8*(6-K)
      SID(K)=SMIN+E/39.*(SMAX-SMIN)
      DO 95 J=1,8
      N=N+1
      NA(1)=1
      NA(2)=1
      M1=0
      DO 96 I=2,99
      TMP  =(VAL(I)-SMIN)/(SMAX-SMIN)*39.+1.
      L=TMP
      L=41-L
      IF(N.NE.L) GO TO 96
      CALL ATHRUZ(O(I),1H*)
      M1=M1+1

```

```

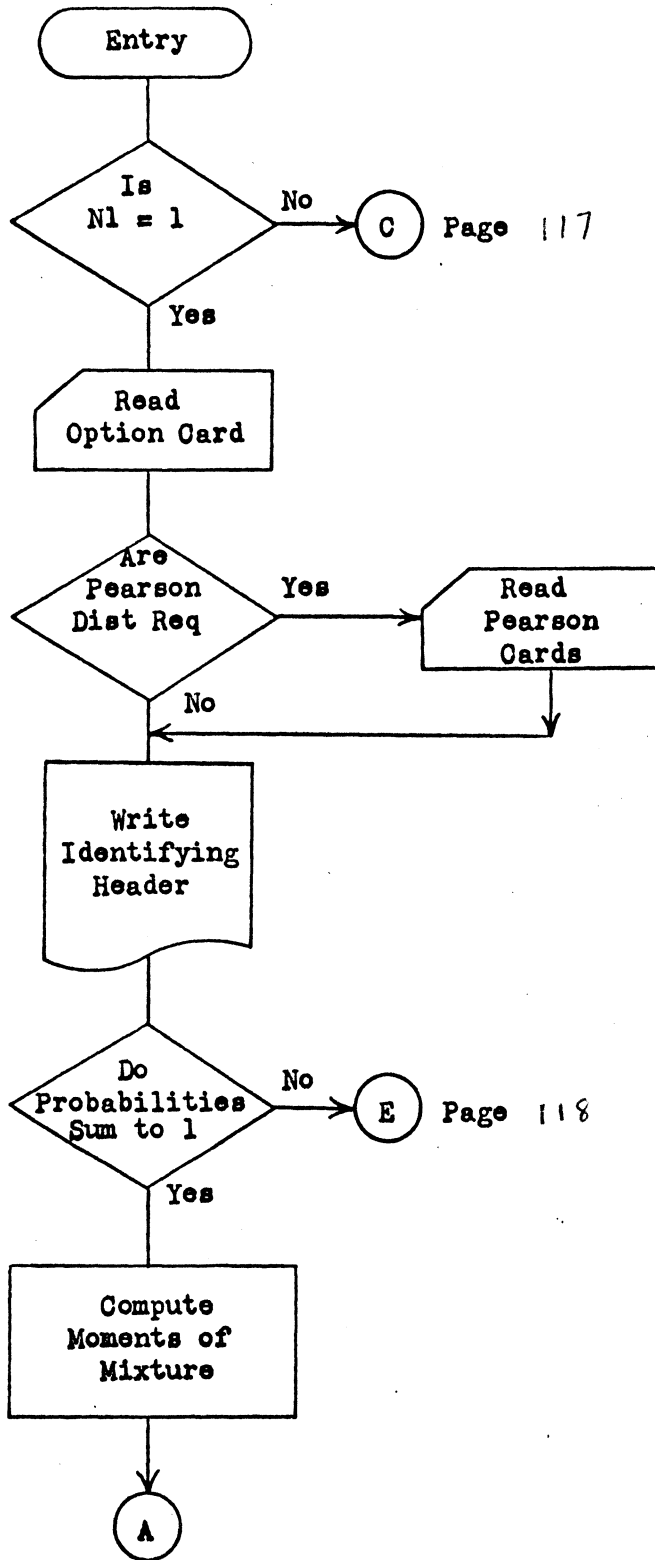
PURGE593
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PURGE629

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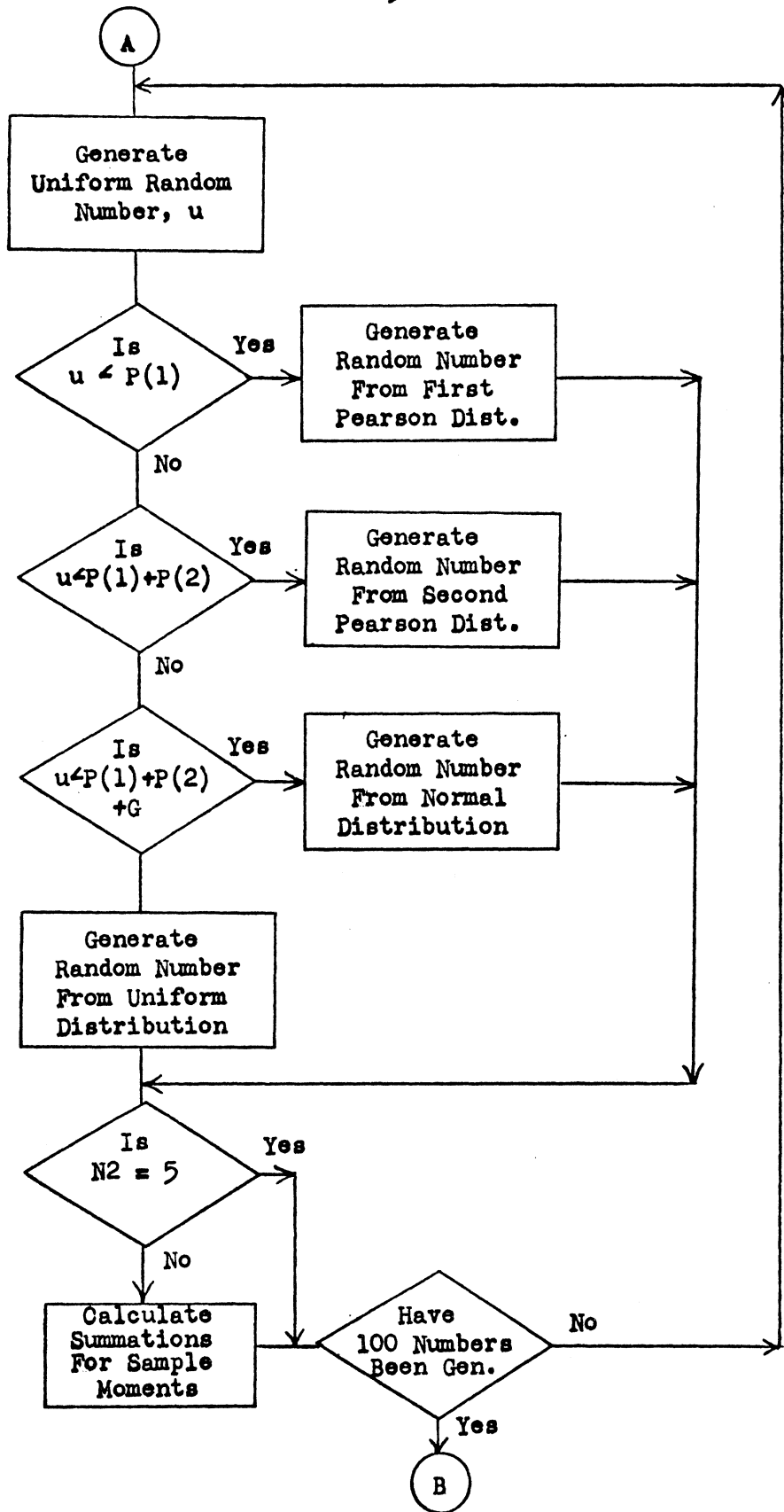
96	NA(M1)=I CONTINUE GO TO (97,98,98,98,98,98,98,98),J	PURGE630 PURGE631 PURGE632
97	WRITE (L3,99) SID(K),(O(I),I=1,100)	PURGE633
99	FORMAT(2X,E9.2,2H +,100A1) GO TO 65	PURGE634 PURGE635
98	WRITE(L3,66) (O(I),I=1,100)	PURGE636
66	FORMAT(13X,100A1)	PURGE637
65	DO 95 I=1,M1 L=NA(I)	PURGE638 PURGE639
95	CALL ATHRUZ(O(L),1H)	PURGE640
C		PURGE641
C		PURGE642
	WRITE (L3,67)(BOT(I),I=10,90,10)	PURGE643
67	FORMAT (/13X,9(9X,1H+)/20X,9E10.3)	PURGE644
	RETURN	PURGE645
C		PURGE646
	750 WRITE(L3,751) BETA1,BETA2	PURGE647
	751 FORMAT(3X,2F18.8,29H ILLEGAL VALUES FOR B1 AND B2)	PURGE648
	GO TO 983	PURGE649
903	WRITE (L3,904)D1,D2	PURGE650
904	FORMAT (3X,2F18.8,29H ILLEGAL VALUES FOR M1 AND M2)	PURGE651
	GO TO 983	PURGE652
906	WRITE (L3,907)B1,B2	PURGE653
907	FORMAT (3X,2F18.8,29H ILLEGAL VALUES FOR A1 AND A2)	PURGE654
	GO TO 983	PURGE655
910	WRITE (L3,911)	PURGE656
911	FORMAT (3X,33HTOO MUCH AND / OR TOO LARGE DATUM)	PURGE657
C		PURGE658
	983 LIMIT=0	PURGE659
	RETURN	PURGE660
605	STOP	PURGE661
	END	PURGE662

ERROR NOTIFICATION

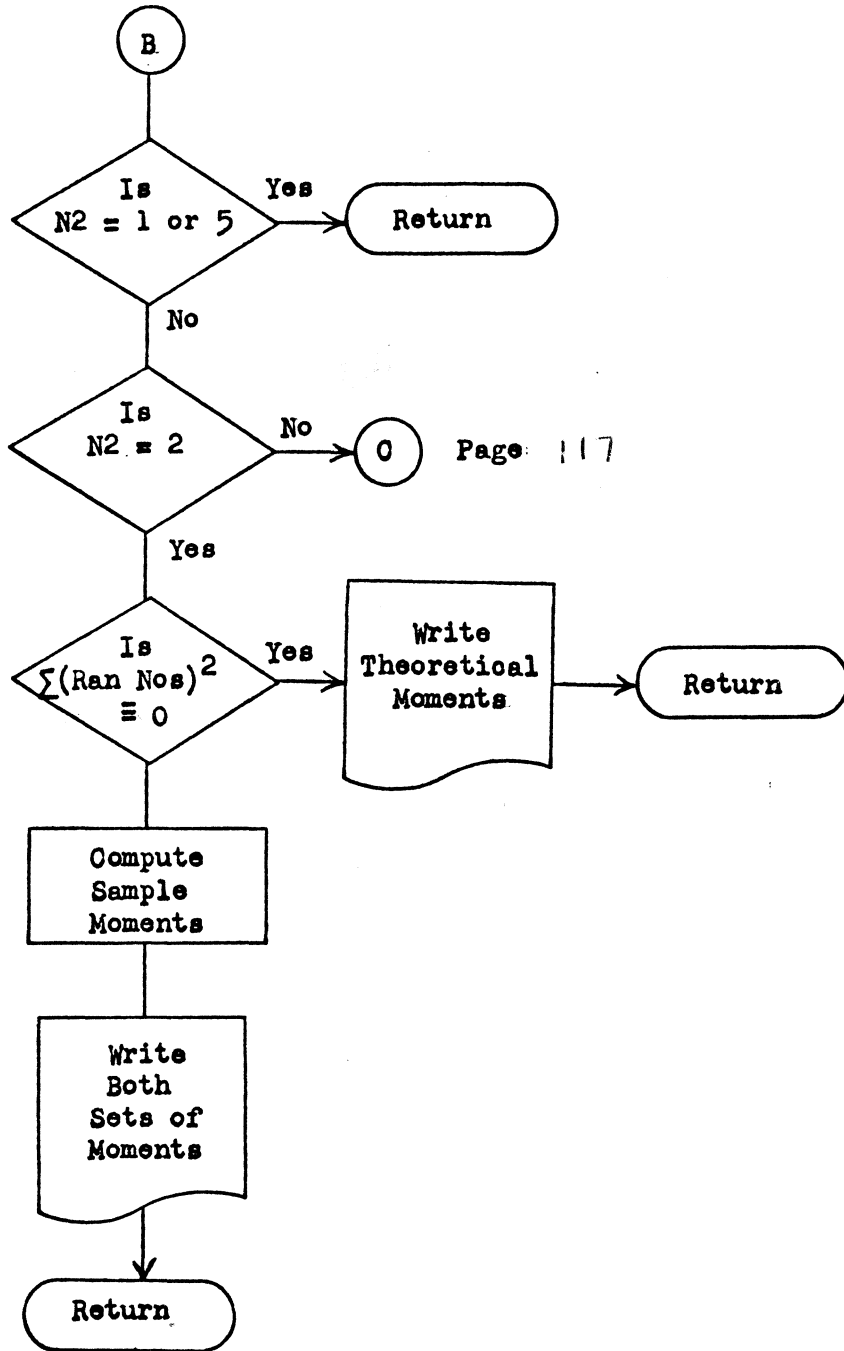
TO NXT PASS



Flowchart For MIX

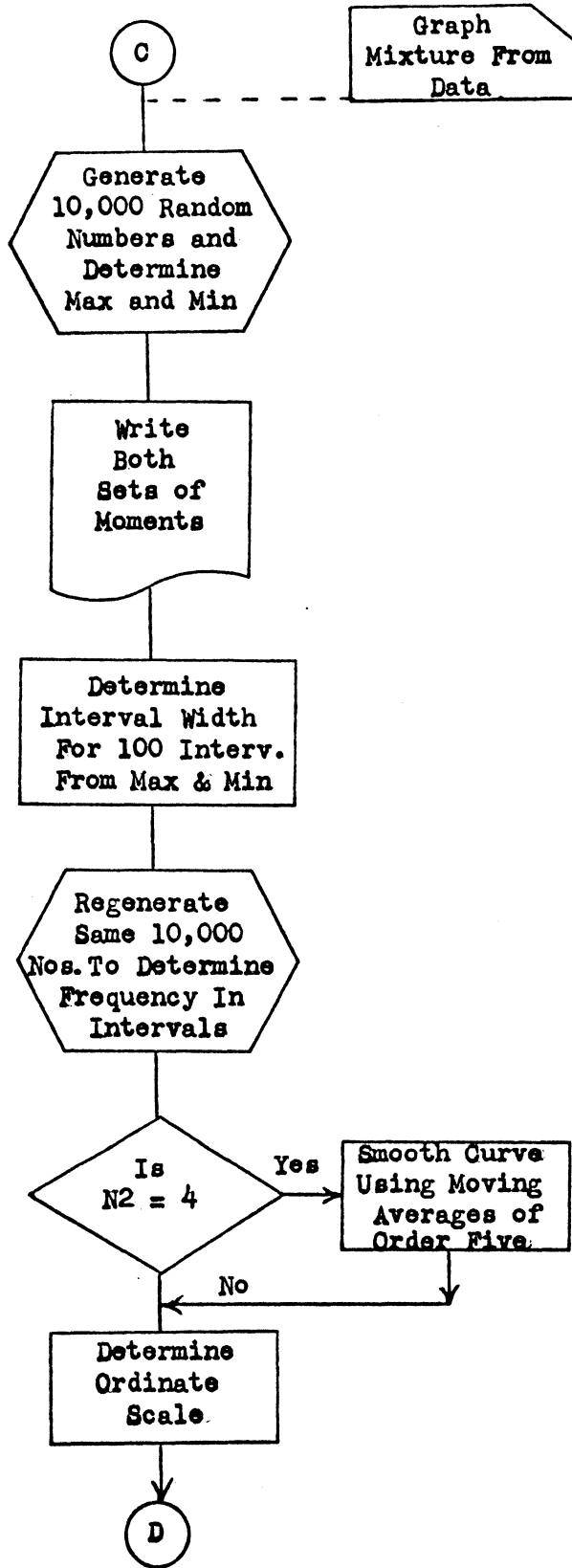


Flowchart For MIX, etc.

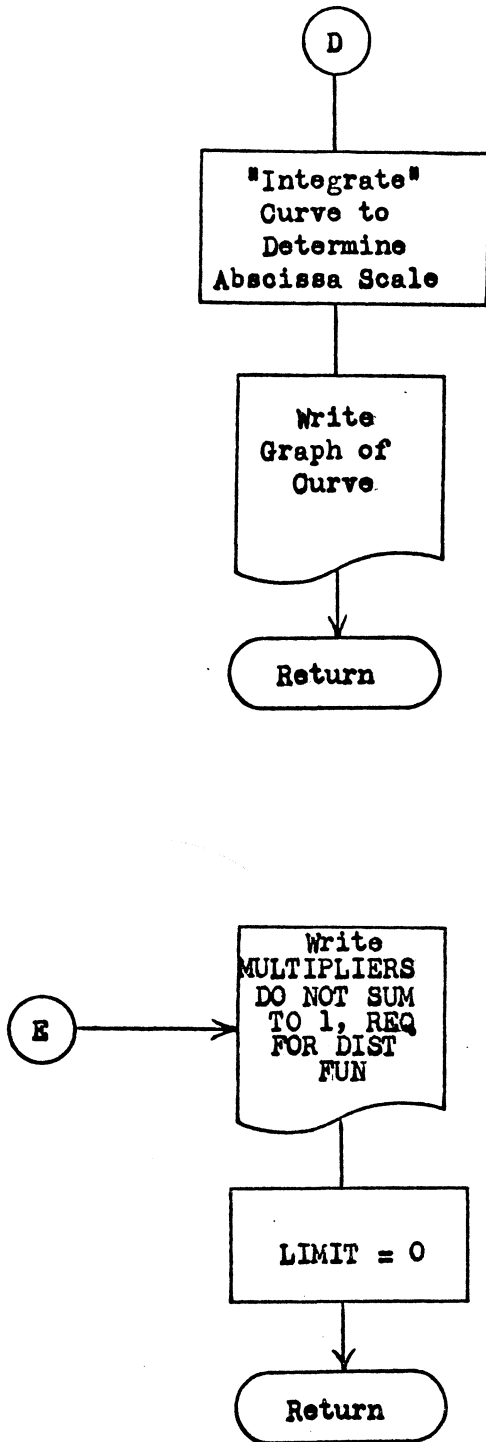


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Flowchart For MIX, etc.



Flowchart For MIX, ctd.



Flowchart For MIX, ctd.

	K=N(I)		MIX038
	102 READ(5) (S(I,J),J=1,K)		MIX039
	110 WRITE(6,125) P(1),P(2),G,GM,GV,U,UL,UP		MIX040
	125 FORMAT(1H1,92X,21HDISTRIBUTION MIXTURES/13H0CONTROL CARD,6H P1=,		MIX041
	1,F10.4,6H P2=,F10.4,6H NORM=,F10.4,6H MEAN=,F12.5,6H VAR=,F12.5		MIX042
	2/1H0,12X,6H UNIF=,F10.4,6H FROM,F10.4,6H TO,F10.4)		MIX043
	IF(ABS(1.-P(1)-P(2)-G-U) .GE. .001) GO TO 100		MIX044
	IF(G .EQ. 0.) GO TO 40		MIX045
C		FOR NORMAL	MIX046
	IF(NR1 .NE. 1) GO TO 160		MIX047
	NR1=0		MIX048
	BG=RNST(Q)		MIX049
160	BG=SQRT(GV)		MIX050
	DG=3.*GV**2		MIX051
40	IF(U .EQ. 0.) GO TO 41		MIX052
C		COMPUTE CENTRAL MOMENTS FOR UNIFORM	MIX053
	AU=(UL+UP)/2.		MIX054
	BU=(UP-UL)**2/12.		MIX055
	DU=(UP-UL)**4/80.		MIX056
C		COMPUTE NONCENTRAL MOMENTS FOR MIX	MIX057
41	TM1=P(1)*C1(1) + P(2)*C1(2) + G*GM + U*AU		MIX058
	TM2=P(1)*RM2(C1(1),C2(1)) + P(2)*RM2(C1(2),C2(2)) + G*RM2(GM,GV)		MIX059
	1+ U*RM2(AU,BU)		MIX060
	TM3=P(1)*RM3(C1(1),C2(1),C3(1)) + P(2)*RM3(C1(2),C2(2),C3(2)) +		MIX061
	1G*RM3(GM,GV,0.) + U*RM3(AU,BU,0.)		MIX062
	TM4=P(1)*RM4(C1(1),C2(1),C3(1),C4(1)) + P(2)*RM4(C1(2),C2(2),C3(2)		MIX063
	1,C4(2)) + G*RM4(GM,GV,0.,DG) + U*RM4(AU,BU,0.,DU)		MIX064
C		COMPUTE CENTRAL MOMENTS	MIX065
	REWIND 0		MIX066
	WRITE(0) NUMBR		MIX067
	CM2=TM2-TM1**2		MIX068
	CM3=TM3-3.*TM1*TM2+2.*TM1**3		MIX069
	CM4=TM4-4.*TM1*TM3+6.*TM2*TM1**2-3.*TM1**4		MIX070
C		GENERATE RANDOM NOS.	MIX071
	P(2)=P(2)+P(1)		MIX072
	G=G+P(2)		MIX073
	UR=UP-UL		MIX074

```

CALL OVERFL(J3K)
19 GO TO (20,20,503,504,16),N2
16 N1=3
20 DO 393 K=1,LIMIT
GO TO KY,(60,51)
52 IF(RN1 .GE. G) GO TO 53
TOM(K)=(RNOR(0.)*BG)+GM
GO TO 675
53 TOM(K)=RDM(1.0)*UR+UL
GO TO 675
60 RN1=RDM(1.0)
IF(RN1 .GE. P(1)) GO TO 50
M=1
GO TO 51
50 IF(RN1 .GE. P(2)) GO TO 52
M=2
51 RND=RDM(1.0)
NR=INT(100.*RND)+1
L=KU(M,NR)
671 J=N(M)
DO 387 I=L,J
IF(S(M,I)-RND) 387,390,388
387 CONTINUE
388 BUT=FLOAT(I+I-2)-2.*(S(M,I)-RND)/(S(M,I)-S(M,I-1))
C
GO TO 391
390 BUT=I+I-2
391 TOM(K)=EL(M)+BUT*H(M)+C1(M)
675 GO TO (683,683,393),N1
683 DO 685 KK=1,4
685 FAN(KK)=FAN(KK)+ TOM(K)**KK
393 CONTINUE
LT=LT+LIMIT
GO TO (952,400,501,502,952),N2
952 RETURN
C
400 TP=LT

```

CAL OUTPUT MOMENTS

```

MIX075
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MIX077
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MIX108
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MIX110
MIX111

```

	DO 405 KK=1,4	MIX112
405	FA(KK)=FAN(KK)/TP	MIX113
	FCM2=FA(2)-FA(1)**2	MIX114
	FCM3=FA(3)-3.*FA(1)*FA(2)+ 2.*FA(1)**3	MIX115
	FCM4=FA(4)-4.*FA(1)*FA(3) +6.*FA(1)**2*FA(2)-3.*FA(1)**4	MIX116
	CALL OVERFL(J3K)	MIX117
	IF(J3K .EQ. 1) WRITE(6,922)	MIX118
922	FORMAT(6H OVRFL)	MIX119
	IF(FAN(2).EQ.0.) GO TO 148	MIX120
C	WRITE BOTH SETS OF MOMENTS	MIX121
	WRITE(6,410) .LT	MIX122
410	FORMAT(1H0,27X,32HMOMENTS FROM ORIGINAL DATA,6X,19HFROM GENE	MIX123
	1RATED DATA,6H N=,I6)	MIX124
407	WRITE(6,411) TM1,FA(1),CM2,FCM2,CM3,FCM3,CM4,FCM4	MIX125
411	FORMAT(35X,4HMEAN,3X,F18.8,4X,F18.8/31X,8HVARIANCE,3X,F18.8,4X,	MIX126
	2F18.8/34X,5HMU(3),3X,F18.8,4X,F18.8/34X,5HMU(4),3X,F18.8,4X,F18.8/	MIX127
	3)	MIX128
	GO TO 412	MIX129
148	WRITE (6 ,149)	MIX130
149	FORMAT(1H0,51X,17HMOMENTS FROM DATA)	MIX131
	WRITE (6 ,150)TM1 ,CM2,CM3,CM4	MIX132
150	FORMAT (54X,4HMEAN,4X,F18.8 /50X,8HVARIANCE,4X,F18.8 /53X,5HMU(3)	MIX133
	2 ,4X,F18.8 /53X,5HMU(4),4X,F18.8)	MIX134
412	IF(N2.EQ.4) GO TO 75	MIX135
	RETURN	MIX136
C	GRAPH ROUTINE	MIX137
503	ASSIGN 904 TO KS	MIX138
	GO TO 500	MIX139
504	ASSIGN 903 TO KS	MIX140
	N2=3	MIX141
500	DO 1 I=1,100	MIX142
	1 VAL(I)=0.	MIX143
	VAL(101)=0.	MIX144
	SMIN=TM1	MIX145
	SMAX=TM1	MIX146
	Q=RNEX (Z)	MIX147
	REWIND 0	MIX148

```

WRITE(0) NUMBR
LT=0
DO 39 I=1,4
39 FAN(I)=0.
NN=0
70 NN=NN+1
IF(NN .EQ. 101) GO TO 71
GO TO 20
501 DO 3 NR=1,100
IF(TOM(NR) .LT. SMIN) SMIN=TOM(NR)
IF(TOM(NR) .GT. SMAX) SMAX=TOM(NR)
3 CONTINUE
GO TO 70
71 FIL=(SMAX-SMIN)/100.
Z =RNST(Q)
REWIND 0
READ(0) NUMBR
N1=3
N2=4
NN=0
GO TO 400
75 NN=NN+1
IF(NN .EQ. 101) GO TO 76
GO TO 20
502 DO 7 NR=1,100
J=(TOM(NR)-SMIN)/FIL + 1.
7 VAL(J)=VAL(J)+1.
GO TO 75
76 VAL(100)=VAL(100)+VAL(101)
VL=VAL(50)
VS=VL
VLT=0.
X=VAL(1)
Y=VAL(2)
GO TO KS,(903,904)
903 DO 10 I=3,98
TMP=VAL(I)

```

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MIX149
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MIX184
MIX185

```

	VAL(I)=(X+Y+VAL(I)+VAL(I+1)+VAL(I+2))/5.	MIX186
	X=Y	MIX187
10	Y=TMP	MIX188
	VAL(2)=(VAL(1)+VAL(2)+VAL(3))/3.	MIX189
	VAL(99)=(VAL(98)+VAL(99)+VAL(100))/3.	MIX190
904	DO 901 I=1,100	MIX191
	CALL ATHRUZ(O(I),1H)	MIX192
	IF(VAL(I) .GT. VL) VL=VAL(I)	MIX193
	IF(VAL(I).LT.VS) VS=VAL(I)	MIX194
901	CONTINUE	MIX195
C	DET Y SCALE	MIX196
	DO 13 I=1,100	MIX197
13	VLT=VLT+VAL(I)	MIX198
	R=39./(VL-VS)	MIX199
	A=(1./(FIL*VLT*R))*8.	MIX200
	DO 11 I=2,99	MIX201
11	NAL(I)=(VAL(I)-VS)*R + 1.5	MIX202
	DO 12 I=1,9	MIX203
	F=I*10	MIX204
12	BOT(I)=SMIN+F*FIL	MIX205
	M=41	MIX206
	DO 95 K=1,5	MIX207
	E=6-K	MIX208
	SID(K)=A*E	MIX209
	DO 95 J=1,8	MIX210
	M=M-1	MIX211
	NA(1)=1	MIX212
	M1=0	MIX213
	DO 96 I=2,99	MIX214
	IF(M .NE. NAL(I)) GO TO 96	MIX215
	CALL ATHRUZ(O(I),1H*)	MIX216
	M1=M1+1	MIX217
	NA(M1)=I	MIX218
96	CONTINUE	MIX219
	GO TO (97,98,98,98,98,98,98,98),J	MIX220
97	WRITE(6,99) SID(K),(O(I),I=1,100)	MIX221
99	FORMAT(2X,E9.2,2H +,100A1)	MIX222

```
GO TO 65
98 WRITE(6,66) (O(I),I=1,100)
66 FORMAT (13X,100A1)
65 DO 95 I=1,M1
L=NA(I)
95 CALL ATHRUZ(O(L),1H )
WRITE(6,67) (BOT(I),I=1,9)
67 FORMAT (//13X,9(9X,1H+)/20 X,9E10.3)
RETURN
```

C

ERROR NOTIFICATION

```
100 WRITE(6,120)
120 FORMAT(1H0,30X,39HMPYRS DO NOT SUM TO 1, REQ FOR DIST FUN)
LIMIT=0
RETURN
END
```

```
MIX223
MIX224
MIX225
MIX226
MIX227
MIX228
MIX229
MIX230
MIX231
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MIX234
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MIX236
MIX237
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ABSTRACT

This thesis contains a brief review of some of the work that has been done concerning the generation and testing of pseudo-random numbers. Computer subroutine programs written in FORTRAN IV are given for the generation of pseudo-random numbers from Pearson distributions as well as from any combination of mixtures of two Pearson distributions, a normal distribution with arbitrary mean and variance and a uniform distribution on any finite interval.

The Pearson distribution may be specified either by the first four moments or from sample data, then the parameters of the fitted distribution are printed and, if desired, a graph of the distribution. A graph of the mixture of distributions may be obtained from 10,000 pseudo-random numbers from the mixture.

The speed of generation varies from about 10,000 random numbers per minute (on the IBM 7040), for a Pearson distribution with moments calculated from the generated numbers, to more than 100,000 numbers per minute if mixtures are used.

The subroutines are applied to a Monte Carlo investigation of the robustness of several methods of confidence interval estimation.