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**TEXAS A&I UNIVERSITY**



**Kingsville, Texas**

TECHNICAL REPORT #3

INVESTIGATION OF THE SPECHT  
DENSITY ESTIMATOR

DEPARTMENT OF  
MATHEMATICS

TEXAS A&I UNIVERSITY

RESEARCH GRANT #NGR 44-073-003

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INVESTIGATION OF THE SPECHT

DENSITY ESTIMATOR

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July, 1971

DEPARTMENT OF  
MATHEMATICS

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## DENSITY ESTIMATION

The purpose of this project is to determine the feasibility of using the Specht density estimator function on the IBM 360/44. Factors such as storage, speed, amount of calculations, size of the smoothing parameter and sample size have an effect on our results. We want to (1) investigate the reliability of the Specht estimator for normal and uniform distributions and (2) show the effects of the smoothing parameter and sample size.

The Specht function which is supposed to estimate a density distribution of an  $m$  dimensional random variable, is as follows:

$$f_i(x) = \frac{1}{(2\pi s)^{m/2}} \cdot \frac{1}{K_i} \sum_{j=1}^{K_i} \text{Exp} \left[ \frac{-(x - A_{ij})^T (x - A_{ij})}{2s} \right]$$

where  $A_{ij}$   $i = 1, \dots, r$  (pattern classes)

$j = 1, \dots, k$ , are the  $m$ -dimensional samples from  
the  $i^{\text{th}}$  class

$s$  is the data-dependent smoothing parameter set by the user.

$X$  is a given vector

$T$  denotes the transpose of a vector.

The Specht function, supposedly has the necessary mathematical properties of a probability density estimator. It

is non-negative for any value of  $x$  and it integrates to unity over the entire space. As  $s \rightarrow 0$  and the number of training samples increases without limit, the Specht function becomes identical to the true probability density.

In the Sept. 1968 Laboratory for Agricultural Remote Sensing Research Bulletin (LARS) No. 844, two disadvantages are (1) the storage of the entire training sample and (2) the amount of computation required for each classification. The LARS suggests a version of the Specht estimator to eliminate these problems as follows:

$$f_1(x) = \frac{c}{K_1} \sum_{j=1}^{K_1} \exp \left[ \frac{-A_j^T A_j}{2s} \right] \exp \frac{A_j^T x}{s}$$

where  $c = (2\pi s)^{-m/2} \exp \left[ \frac{x^T x}{2s} \right]$ , (see Appendix A for derivation).

After the first run, this function was corrected by replacing  $A_j$  with  $A_{1j}$  and by inserting the necessary minus sign in the value of  $c$  so that

$$c = 2\pi s^{-m/2} \exp \left[ \frac{-x^T x}{2s} \right]$$

To examine the feasibility of using the function suggested by Specht and simplified by LARS, a Fortran IV program was written and run on the IBM 360/44. This program utilized the IBM Subroutines Randu and Gauss to generate random variables from uniform and normal distributions respectively. However, later on Randu and Gauss were replaced with better generators,

GEN and RNORM. PLOTK was used to graph the true and estimated functions to show validity of the estimator. A description of the subroutines is given in Appendix B.

To validate the estimator,

$$f_1(x) = \frac{c}{K_1} \sum_{j=1}^{K_1} \exp\left[\frac{-A_j^T A_j}{2s}\right] \exp\left[\frac{A_j^T x}{s}\right]$$

several runs were made varying  $s$ , the smoothing parameter and  $n$ , the number of training samples. When  $s$  was small, .08, and  $N$  large, 500, the absolute value of the argument in the second exponential function became larger than one the machine could handle, i.e. 174.673.

At first this restricted our choices for  $s$  and  $N$  but after investigating the cause we were able to circumvent the problem by using the original Specht estimator. A check was put in the program to set the value of the exponential function equal to zero when the absolute value of the argument,  $\left[\frac{A_j^T x}{s}\right]$ , was greater than 174.673.

The reason we were getting the argument too large was dependent on both  $s$  and  $N$ . The smaller  $s$  became, the smaller a random variable had to be in the training sample to cause the program interupt. As  $N$  became larger, the probability of generating such a number increased.

Consider the following case:

$$S = .07, A(j) = 3.183, N = 500, x = -4.$$

$$\frac{A_j^T x}{s} = \frac{(3.183)(-4)}{.07} < -174.673$$

this value is not negative at all points therefore  $\exp\left[\frac{A_j^T x}{s}\right]$  can't be set to zero. However, if we consider the original estimator we see the argument of the exponential function is negative and this allows us to set the value of the exponential function to zero when its absolute value is greater than 174.673.

Samples of sizes 25,50,100,200,500,1000,2000, and 7000 of normally distributed numbers were generated using GEN and RNORM. The true normal density function was also evaluated at each point  $x$ . Then these two values were graphed and the maximum absolute value of the difference between them was calculated.

This procedure was followed for different values of  $S$ . We let  $S$  take on the values of .1, .5, .125, .15, .1, .09, .08, .07, .06, .03, and .01.

The accuracy of the Specht estimator can be seen in the graphs in Appendix C. These results indicate that our best choice for  $S$  was .01 when  $N$  equalled 7000. For small sample sizes the value of  $s$  has very little effect. In fact some runs showed  $S = 1$ ,  $N = 25$  was better than  $S = 1$ ,  $N = 50$ , 100, or 200.

So as stated, the Specht estimator approaches the true distribution as  $S \rightarrow 0$  and  $N \rightarrow \infty$ .

Another program was written to use the Specht estimator to generate a uniform distribution. As our graphs reveal, the Specht estimator did not yield a uniform distribution.

We let  $S = .09, .1, .15, .125, \text{ and } .5$  and  $N = 100, 200, 500, 1000, \text{ and } 7000$ . The results of these runs were very unsatisfactory. Other runs were made yielding similar results. Graphs 15, 16, 17 show what happens for  $N = 7000$  and  $S = .09, .1, .15$ .

#### CONCLUSION

This preliminary study shows that the Specht estimator is highly dependent upon the choice of  $N$  and  $S$ . As  $N$  gets large, it is still necessary to choose  $S$  with care. A too small choice of  $S$  will produce very bad results. While the Specht estimator does a fair job of estimating the normal distribution, it is poor for estimating the uniform density. A more detailed study is being done to compare this estimator with other estimators found in the literature.



## APPENDIX A

The probability densities are estimated by functions of the form:

$$f_1(x) = \frac{1}{(2\pi s)^{m/2}} \cdot \frac{1}{K_1} \sum_{j=1}^{K_1} \text{EXP} \left[ -\frac{(x - A_{1j})^T(x - A_{1j})}{2s} \right] \quad (1)$$

$$\begin{aligned} \text{EXP}[(x - y)^T(x - y)] &= \text{EXP}[(x^T - y^T)(x - y)] \\ &= \text{EXP}[x^T x - x^T y - y^T x + y^T y] \\ &= \text{EXP}[x^T x - 2y^T x + y^T y] \\ &= \text{EXP}[x^T x] \text{EXP}[-2y^T x] \text{EXP}[y^T y] \end{aligned}$$

$$\begin{aligned} \text{Now } \text{EXP} \left[ \frac{-(x - A_{1j})^T(x - A_{1j})}{2s} \right] &= \text{EXP} \left[ \frac{-x^T x}{2s} \right] \text{EXP} \left[ \frac{2A_{1j}^T x}{2s} \right] \text{EXP} \left[ \frac{-A_{1j}^T A_{1j}}{2s} \right] \\ &= \text{EXP} \left[ \frac{-x^T x}{2s} \right] \text{EXP} \left[ \frac{A_{1j}^T x}{s} \right] \text{EXP} \left[ \frac{-A_{1j}^T A_{1j}}{2s} \right] \end{aligned}$$

Now Eq(1) can be written:

$$\begin{aligned} f_1(x) &= \frac{1}{(2\pi s)^{m/2}} \cdot \frac{1}{K_1} \sum_{j=1}^{K_1} \text{EXP} \left[ \frac{-x^T x}{2s} \right] \text{EXP} \left[ \frac{A_{1j}^T x}{s} \right] \text{EXP} \left[ \frac{-A_{1j}^T A_{1j}}{2s} \right] \\ &= \frac{1}{(2\pi s)^{m/2}} \cdot \frac{1}{K_1} \text{EXP} \left[ \frac{-x^T x}{2s} \right] \sum_{j=1}^{K_1} \text{EXP} \left[ \frac{A_{1j}^T x}{s} \right] \text{EXP} \left[ \frac{-A_{1j}^T A_{1j}}{2s} \right] \end{aligned}$$

$$\text{Now let } c = \frac{1}{(2\pi s)^{m/2}} \text{EXP} \left[ \frac{-x^T x}{2s} \right]$$

And then Eq(1) can be written:

$$f_1(x) = \frac{c}{K_1} \sum_{j=1}^{K_1} \text{EXP} \left[ \frac{A_{1j}^T x}{s} \right] \text{EXP} \left[ \frac{-A_{1j}^T A_{1j}}{2s} \right]$$

## APPENDIX B

This appendix contains a discription of the subroutines used in this report as well as a listing of each program.

These programs include:

- 1) GEN
- 2) RNORM
- 3) PLOTK

```
SUBROUTINE GEN(IL,IX,IY,U,YFL)
```

where

$$IL = 2^9 + 1$$

IX - initial value

IY - replaces IX for the next random number

$$U = 3$$

YFL - Random number from uniform distribution

```
SUBROUTINE GEN(IL,IX,IY,U,YFL)
```

$$IY = IL * IX + U$$

IF(IY)5,6,6

5  $IY = IY + 2147483647 + 1$

6  $YFL = IY$

$$YFL = YFL * .4656613E - 9$$

RETURN

END

```
SUBROUTINE RNONM(AM,S,IX,RN1,RN2)
```

where

AM - is the mean of the distribution

S - is the standard deviation

IX - is used to initialize GEN

RN1  
RN2 - is the pair of normally distributed random numbers

```
SUBROUTINE RNORM(AM,S,IX,RN1,RN2)
```

```
Call GEN(IL,IX,IY,U,U1)
```

```
IX = IY
```

```
Call GEN(IL,IX,IY,U,U2)
```

```
PI2 = (3.14159)*2
```

```
Z = SQRT(-2.*S*ALOG(U1))
```

```
RN1 = Z*COS(PI2*U2) + AM
```

```
RN2 = Z*SIN(PI2*U2) + AM
```

```
RETURN
```

```
END
```

SUBROUTINE PLOTK(T,SS,N,NP,NA,NV,NAME)

PURPOSE - Plot the data points in an array.

T - Is an array in the main program which holds the type of distribution to be printed in the heading.

SS - This is the user supplied smoothing parameter to be printed in the heading.

N - This is the user supplied number of training points to be printed in the heading.

NP - The number of points to be plotted, less than or equal to 100.

NA - The length of the array.

NV - Number of columns in array (Number of variables to be graphed, 1st. one is the abscissa, 2nd. one plotted as 1)

NAME - Is an array that holds the data points to be plotted.

	SUBROUTINE PLOTK(T,SS,N,NP,NA,NV,NAME)	002760
	INTEGER P	002770
	REAL NAME (100)	002780
	DIMENSION DF(20)	002790
	DIMENSION SCALE(6),LINE(103),INJ(9),T(2)	002800
	WRITE(3,12) T,N,SS	002810
12	FORMAT(1H1,T68,'GRAPH'//T50,'PLOTS OF TRUE AND ESTIMATED DENSITY F	002820
	UNCTIONS'/T51,'1 DENOTES TRUE',2A4,', 2 DENOTES ESTIMATED'/T60,N	002830
	2= ',I6,T71,'S =',F5.2)	002840
	KBLNK=1077952576	002850
	KSTAR=1547714624	002860
	INJ(1)=-247447488	002870
	INJ(2)=-230670272	002880
	INJ(3)=-213893056	002890
	INJ(4)=-197115840	002900
	INJ(5)=-180338624	002910
	INJ(6)=-163561408	002920
	INJ(7)=-146784192	002930
	INJ(8)=-130006976	002940
	INJ(9)=-113229760	002950
	KPLUS=1312833600	002960
	KMNUS=1614823488	002970
C	DETERMINE SCALE FACTORS	002980
	K=NA+1	002990
	K1=NA+NP	003000
	YMAX=NAME(K)	003010
	YMIN=NAME(K)	003020
	KV=NV-1	003030
	DO 1000 I=1,KV	003040
	DO 25 J=K,K1	003050
	ARRAY=NAME(J)	003060
	IF(YMAX-ARRAY)10,15,15	003070
10	YMAX=ARRAY	003080
15	IF(YMIN-ARRAY)25,25,20	003090
20	YMIN=ARRAY	003100
25	CONTINUE	003110
	K=((I+1)*NA)+1	003120
	K1=(I+1)*NA+NP	003130
	IF(YMIN .GT. 0.) YMIN = 0.	003140
1000	CONTINUE	003150
	H1=YMAX-YMIN	003160
	H12=H1*.2	003170
	H1=100./H1	003180
	SCALE(1)=YMIN	003190
	DO 30 I=2,6	003200
30	SCALE(I)=SCALE(I-1)+H12	003210
C	PRINT SCALES AND BORDERS	003220
	WRITE(8,1001)SCALE	003230
1001	FORMAT(1HC,12X,F8.2,5(12X,F8.2))	003240
	DO 35 I=1,103	003250
35	LINE(I)=KMNUS	003260
	DO 40 I=2,102,10	003270
40	LINE(I)=KPLUS	003280
	WRITE (8,1002)LINE	003290
1002	FORMAT(9X,'ABS',5X,103A1)	003300
C	PLOT MAIN BODY OF GRAPH	003310
	DO 100 I=1,NP	003320
	DO 102 L=1,103	003330
102	LINE(L)=KBLNK	003340

```
LINE(1)=KMNUS 003350
LINE(103)=KMNUS 003360
X=NAME(I) 003370
K4=NV-1 003380
DO 90 J=1,K4 003390
P=(NA*J)+I 003400
NORMV=(NAME(P)-YMIN)*H1+2.5 003410
IF(NORMV) 200,200,80 003420
200 NORMV = 2 003430
80 LINE(NORMV)=INJ(J) 003440
90 CONTINUE 003450
WRITE(8,1003)X,LINE 003460
1003 FORMAT(3X,F10.2,4X,103A1) 003470
100 CONTINUE 003480
C PRINT BOTTOM LINE AND SCALE 003490
DO 105 I=3,101 003500
105 LINE(I)=KMNUS 003510
DO 110 I=2,102,10 003520
110 LINE(I)=KPLUS 003530
WRITE(8,1002) LINE 003540
WRITE(8,1004) SCALE 003550
1004 FORMAT(12X,F8.2,5(12XF8.2)) 003560
RETURN 003570
END 003580
```

## APPENDIX C

In graphs 1-6, we have held the number of sample points at 7000 and varied the smoothing parameter,  $s$ , from 1. down to .01. It is evident that as  $s$  becomes smaller, our estimated values (graph with 2's) very closely fit the true curve (graphed with 1's).

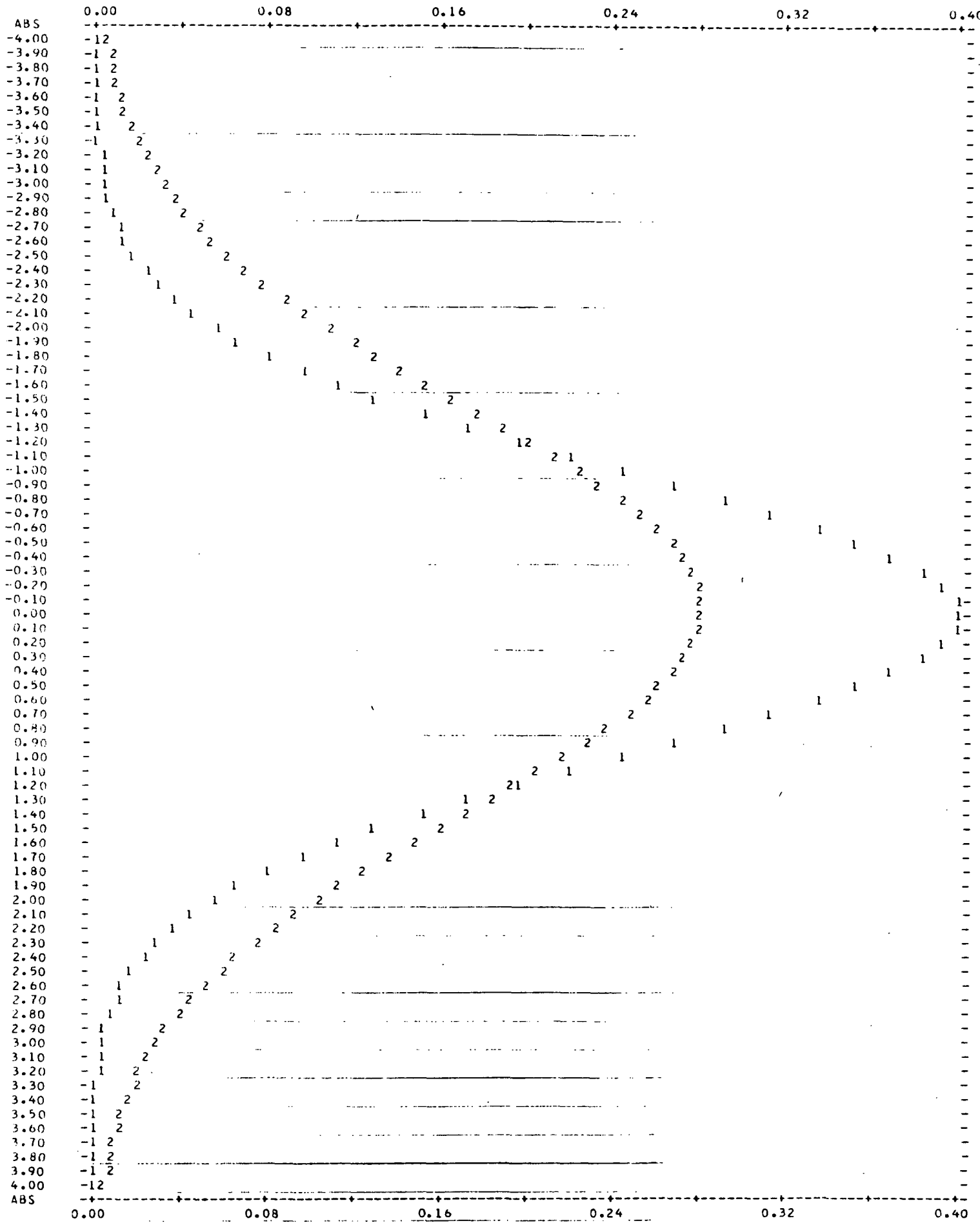
The next set of graphs, 7-10, shows what happens when we fixed  $s$  at .05 and varied  $n$  from 100 to 1000. Graphs 11-14, exhibit the same information for  $s = .07$ .

The next set of graphs 15-17, shows the results of using the Specht estimator to estimate the uniform density. Hence  $N = 7000$ , and  $s = .09, .10, .50$ .



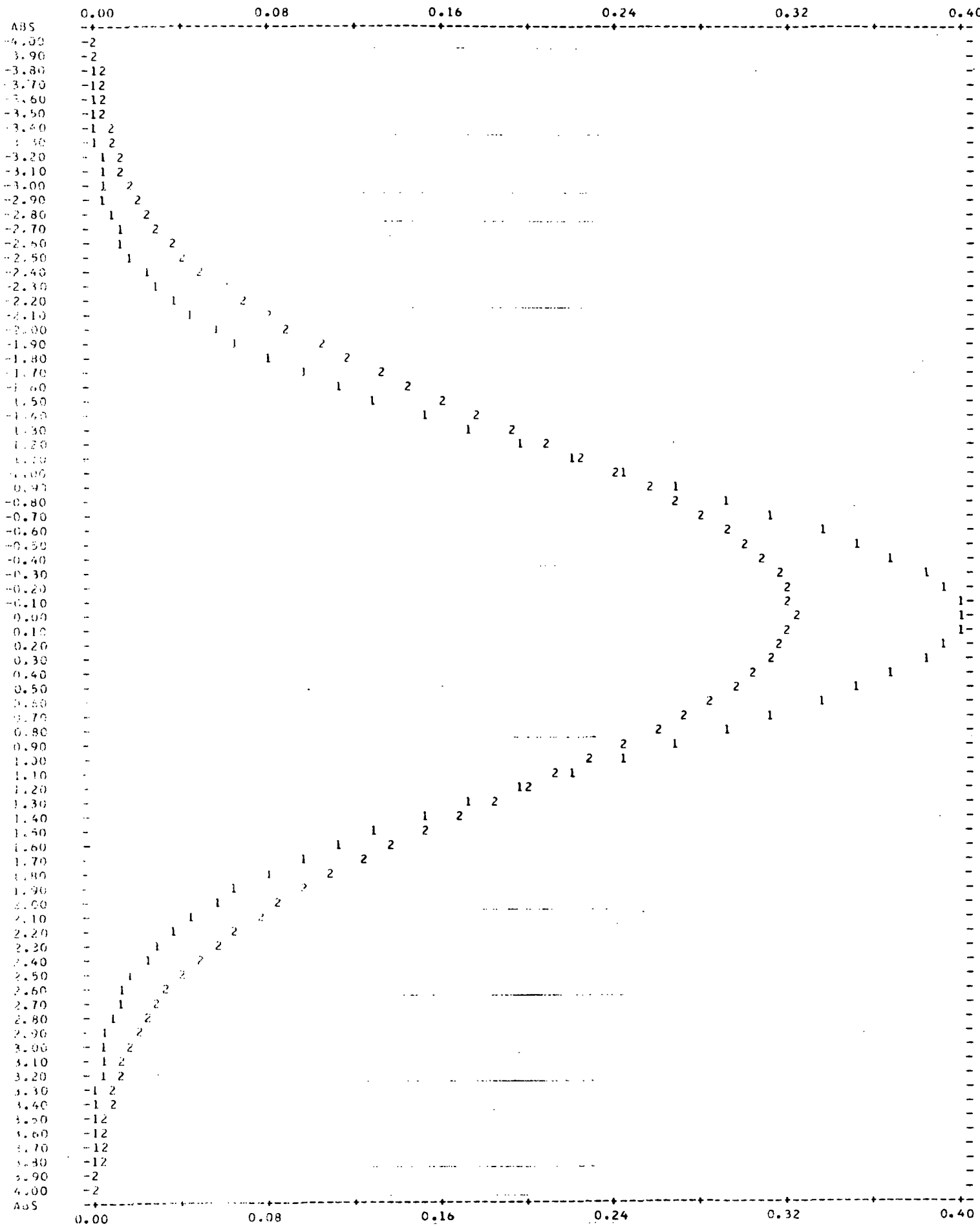
GRAPH 1

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $N(0,1)$ , 2 DENOTES ESTIMATED  
 N = 7000 S = 1.00



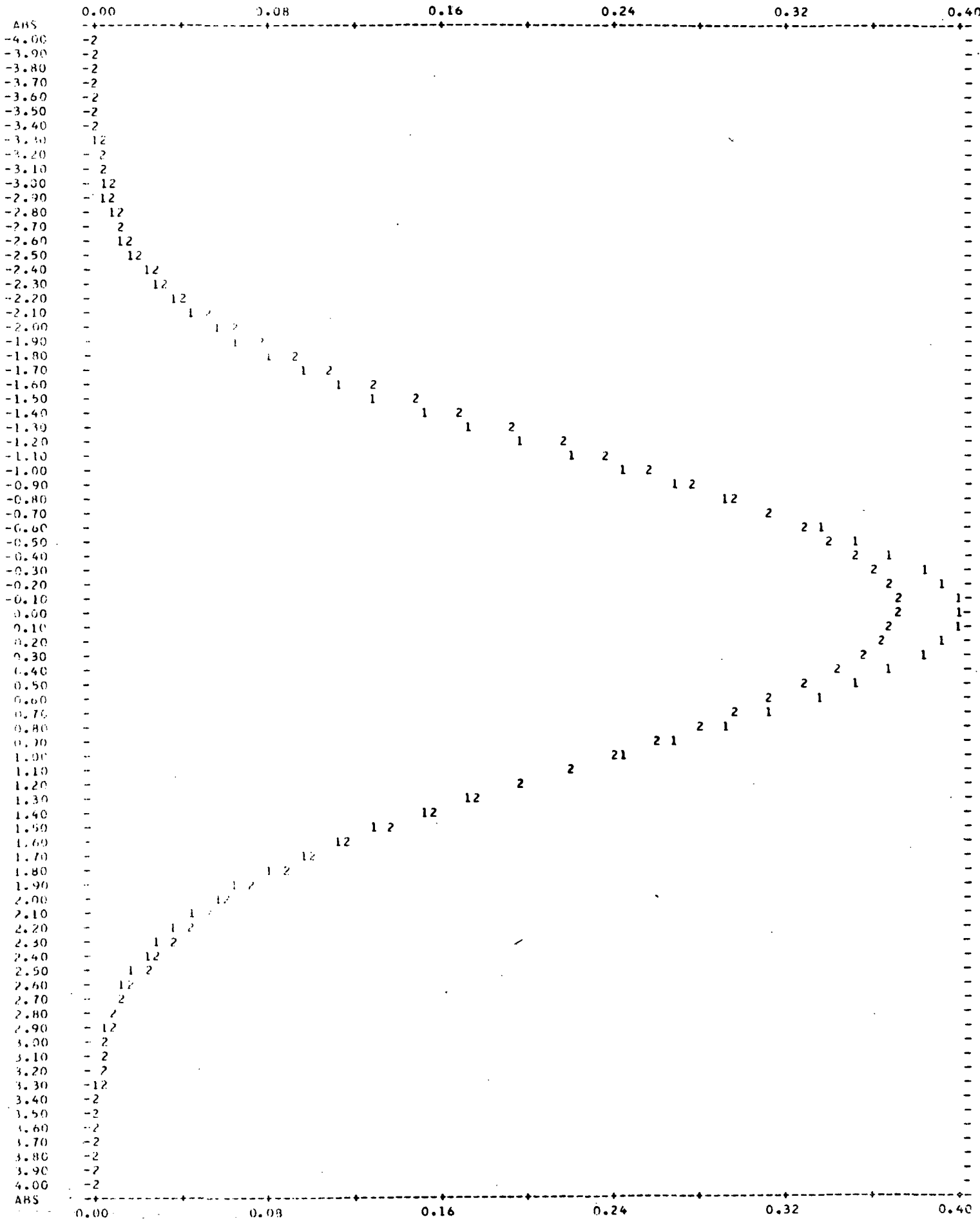
GRAPH 2

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $N(0,1)$ , 2 DENOTES ESTIMATED  
 $N = 7000$   $S = 0.50$



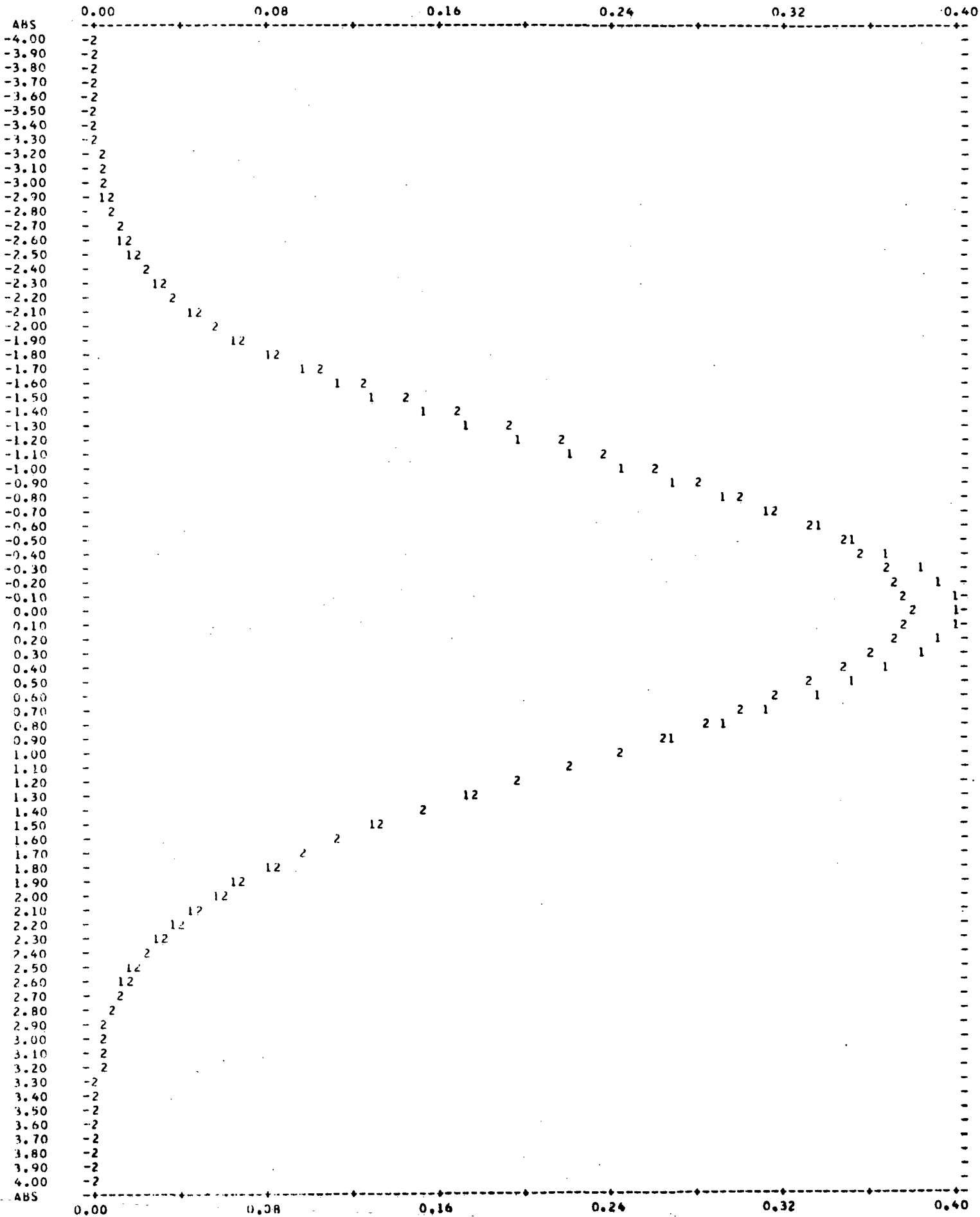
### GRAPH 3

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $N(0,1)$ , 2 DENOTES ESTIMATED  
 $N = 7000 \quad S = 0.10$



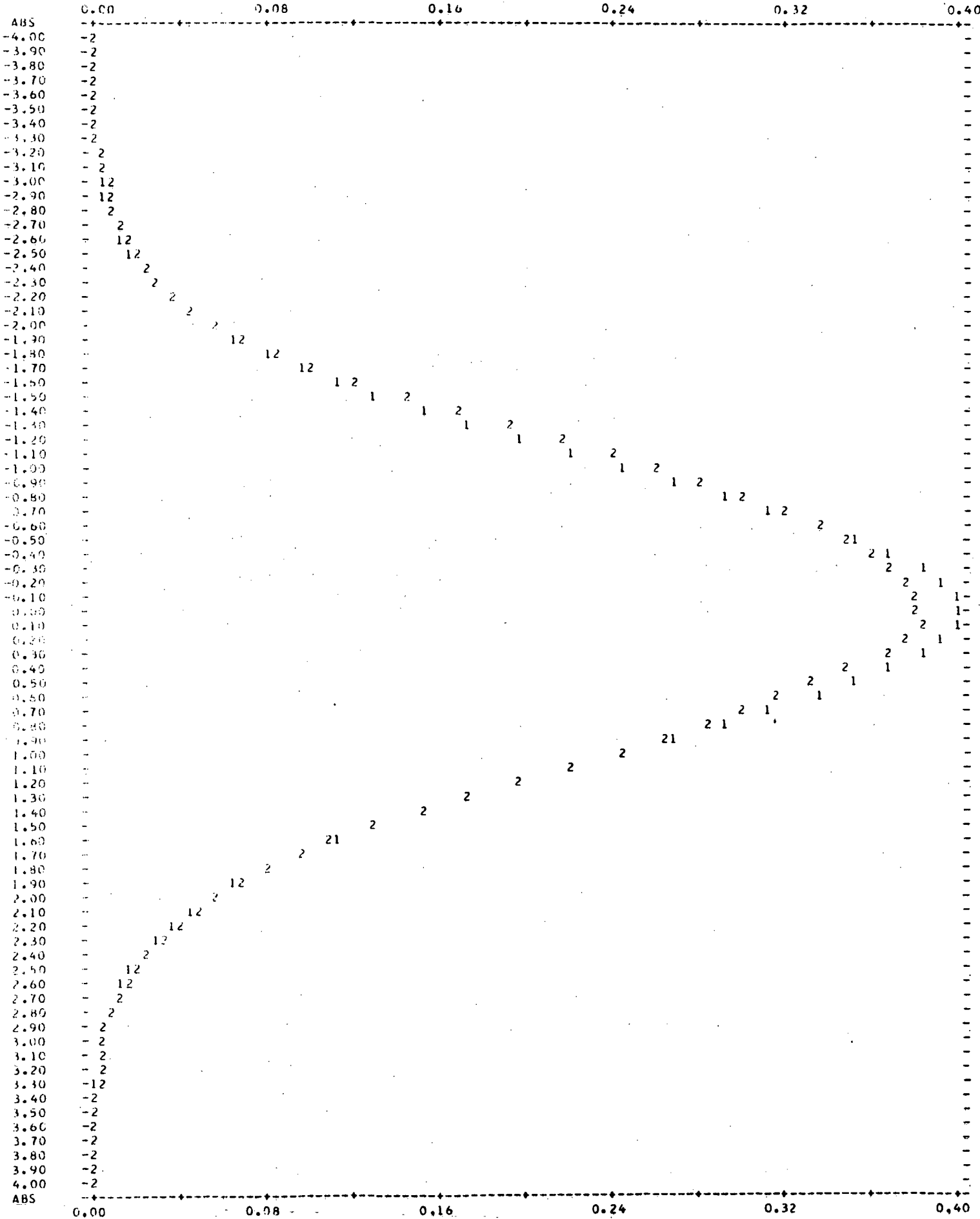
GRAPH 4

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $N(0,1)$  , 2 DENOTES ESTIMATED  
 N = 7000 S = 0.05



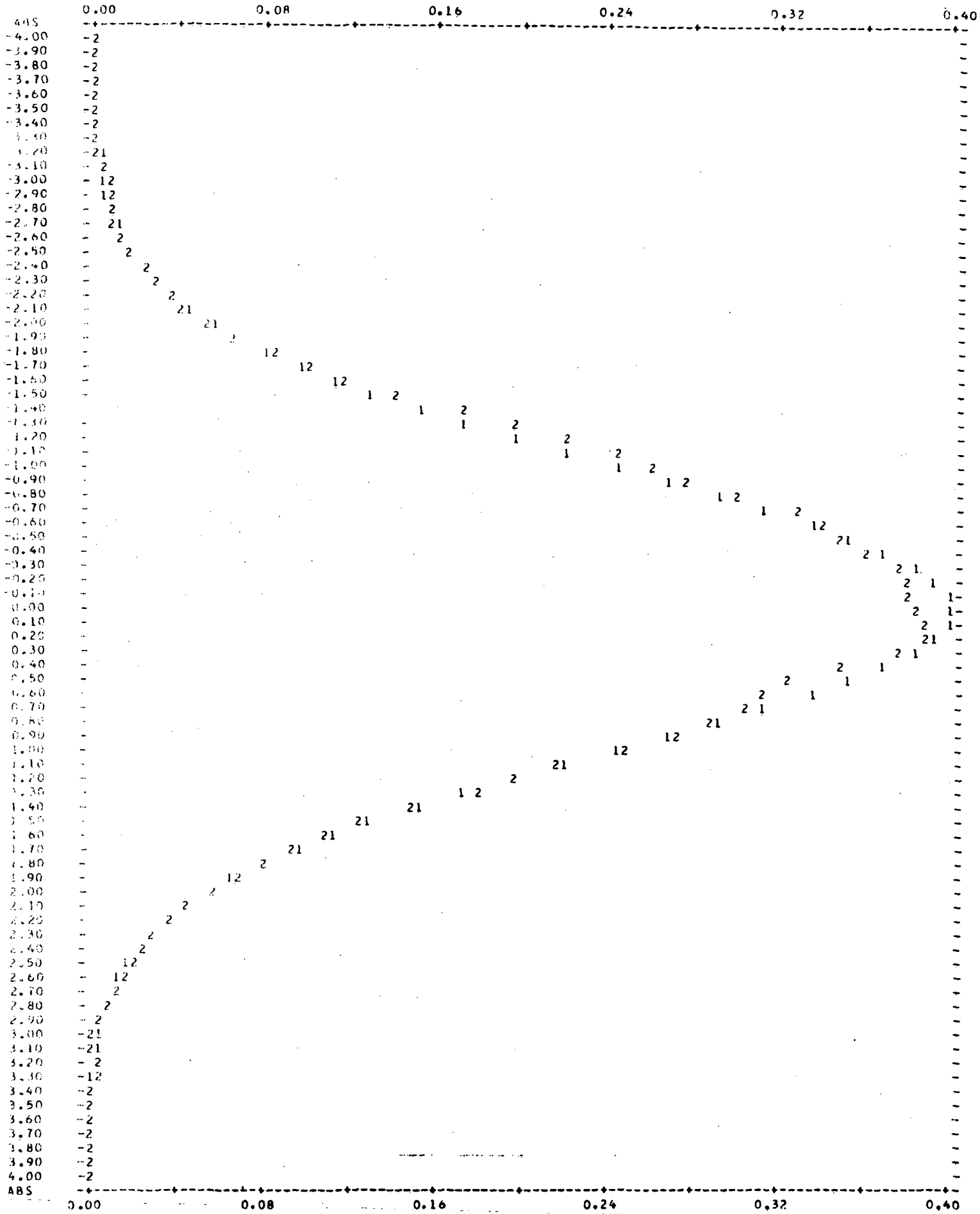
GRAPH 5

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $N(0,1)$ , 2 DENOTES ESTIMATED  
 $N = 7000$   $S = 0.03$



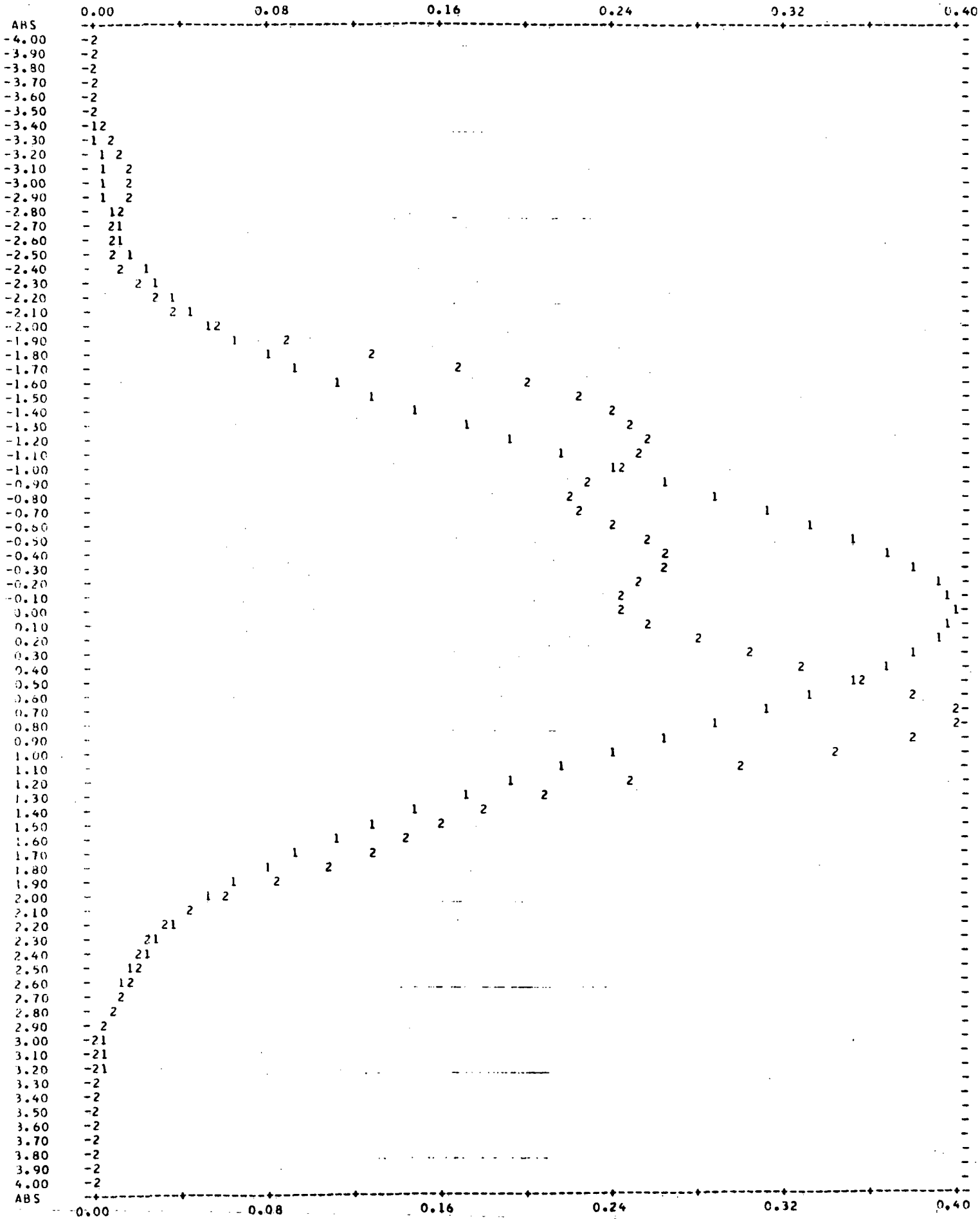
# GRAPH 6

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $N(0,1)$ , 2 DENOTES ESTIMATED  
 $N = 7000$   $S = 0.01$

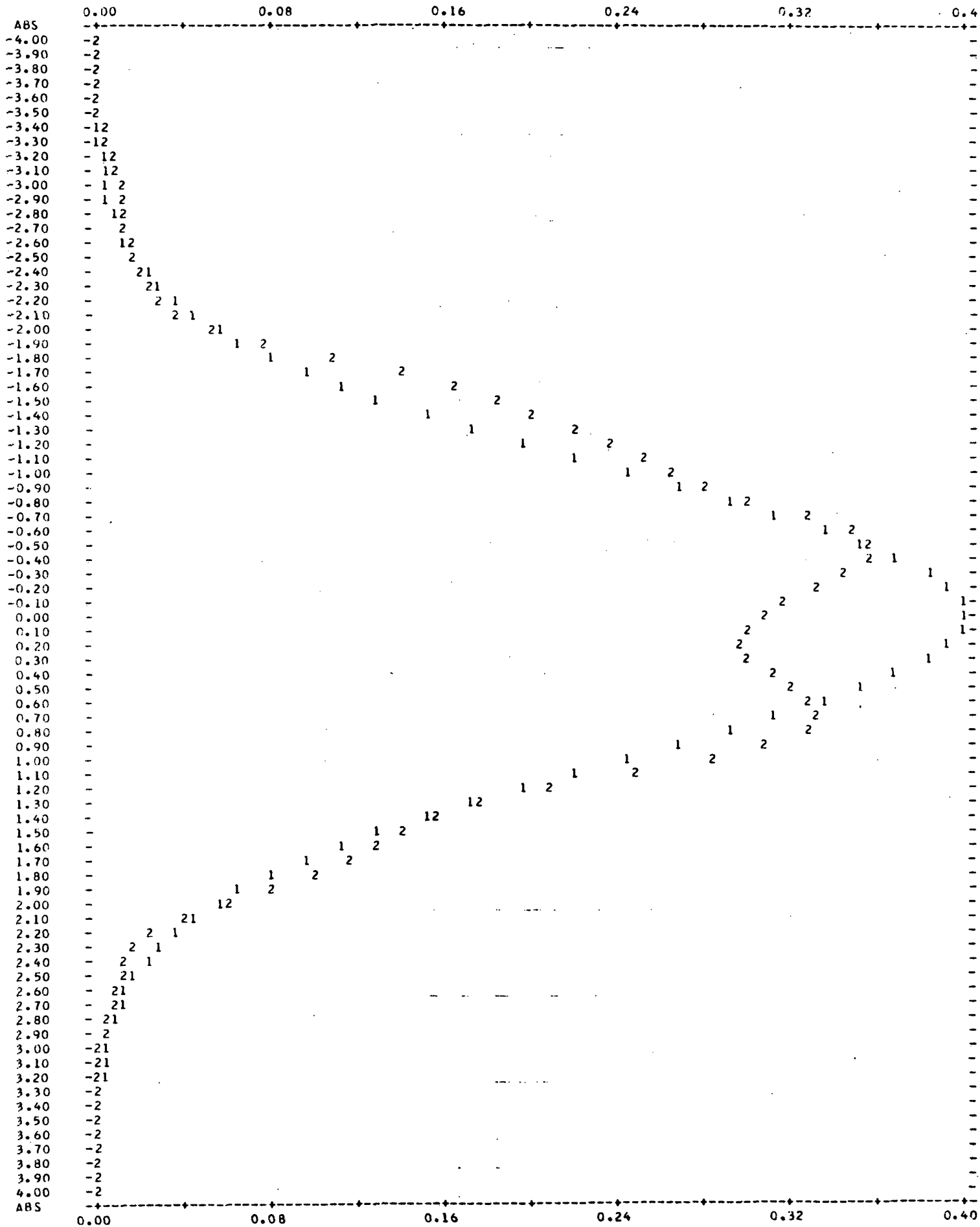


GRAPH 7

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $N(0,1)$ , 2 DENOTES ESTIMATED  
 $N = 100 \quad S = 0.05$



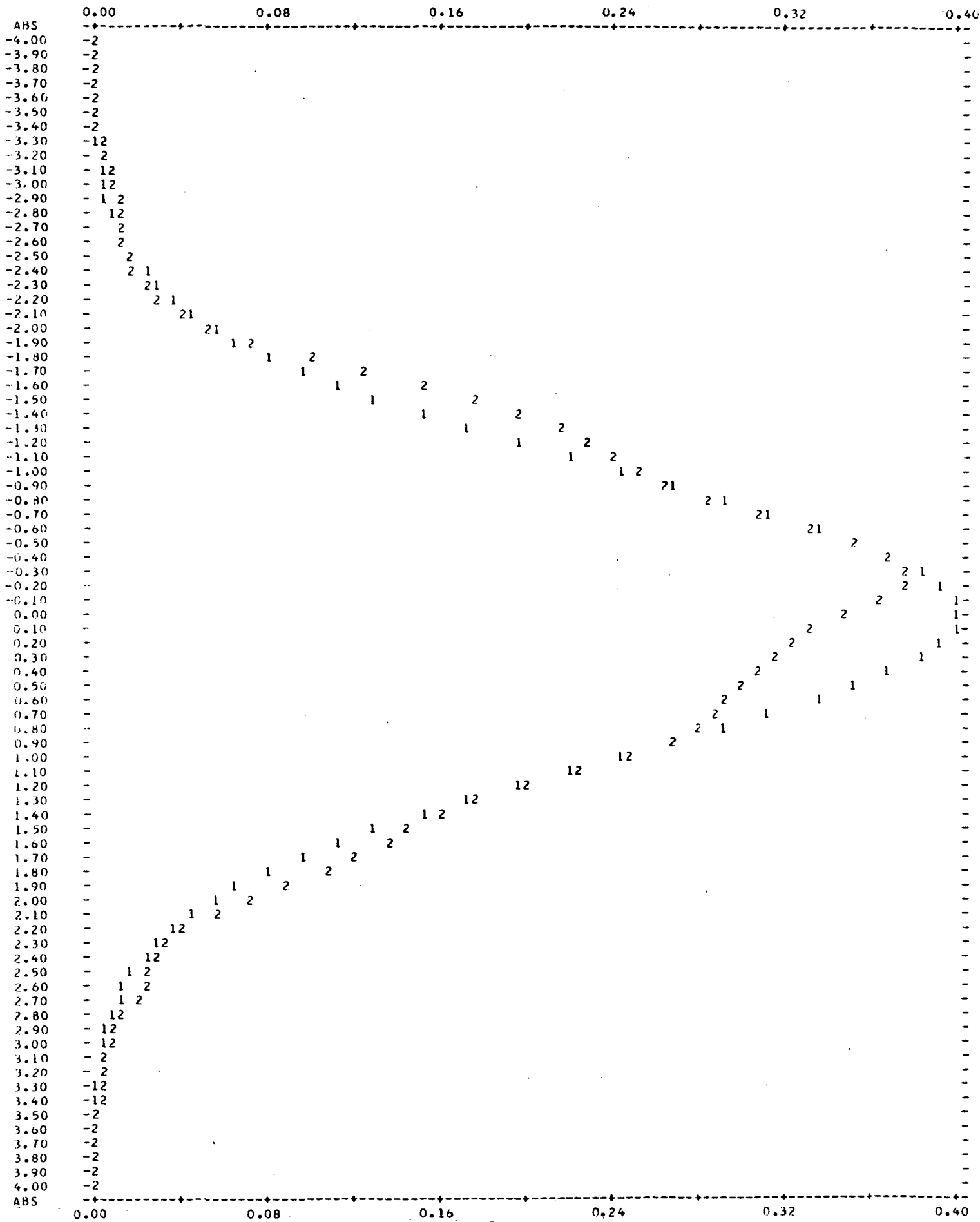
PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE N(0,1), 2 DENOTES ESTIMATED  
 N = 200 S = 0.05





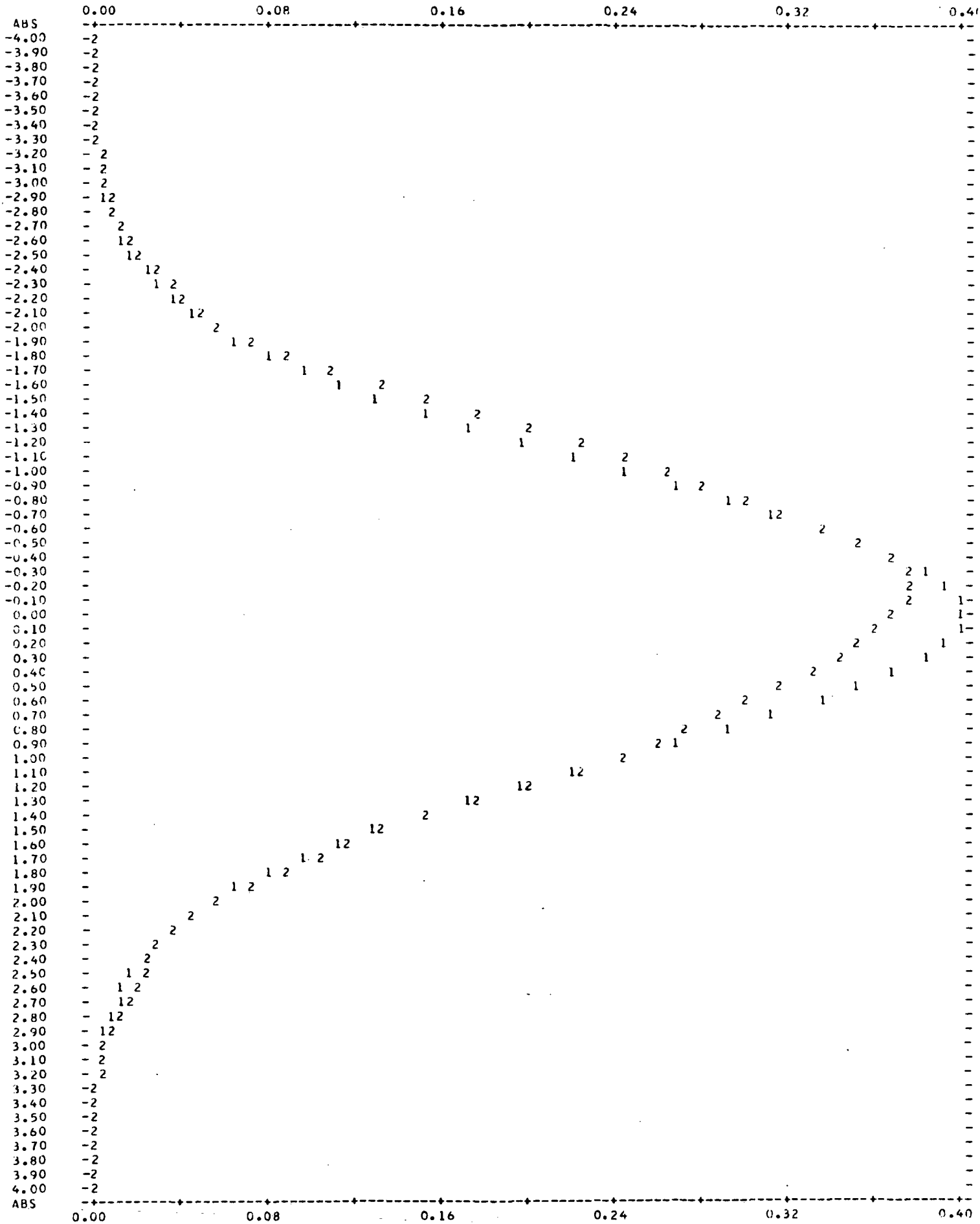
GRAPH 9

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $N(0,1)$ , 2 DENOTES ESTIMATED  
 N = 500 S = 0.05

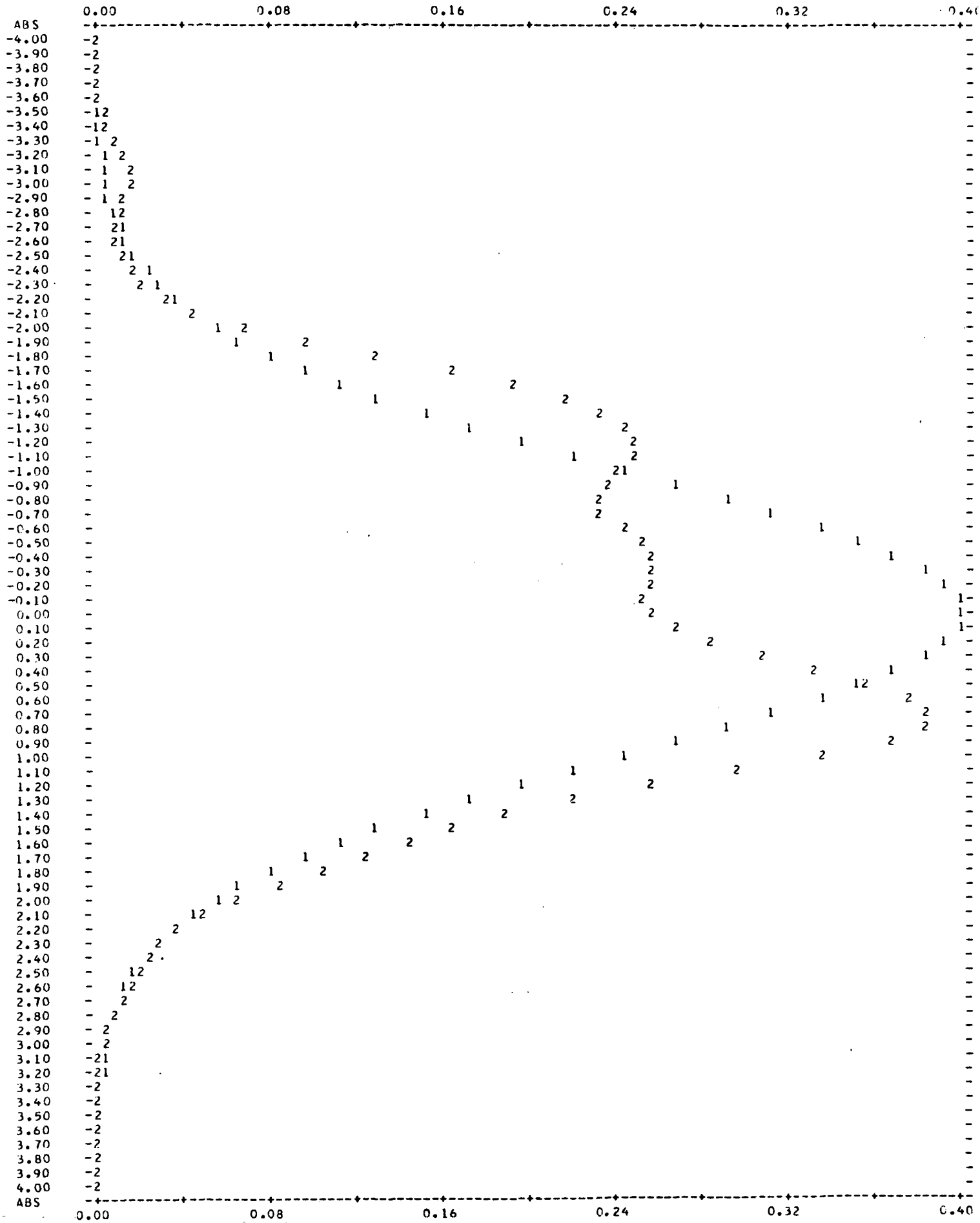


GRAPH 10

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $N(0,1)$ , 2 DENOTES ESTIMATED  
 $N = 1000$   $S = 0.05$

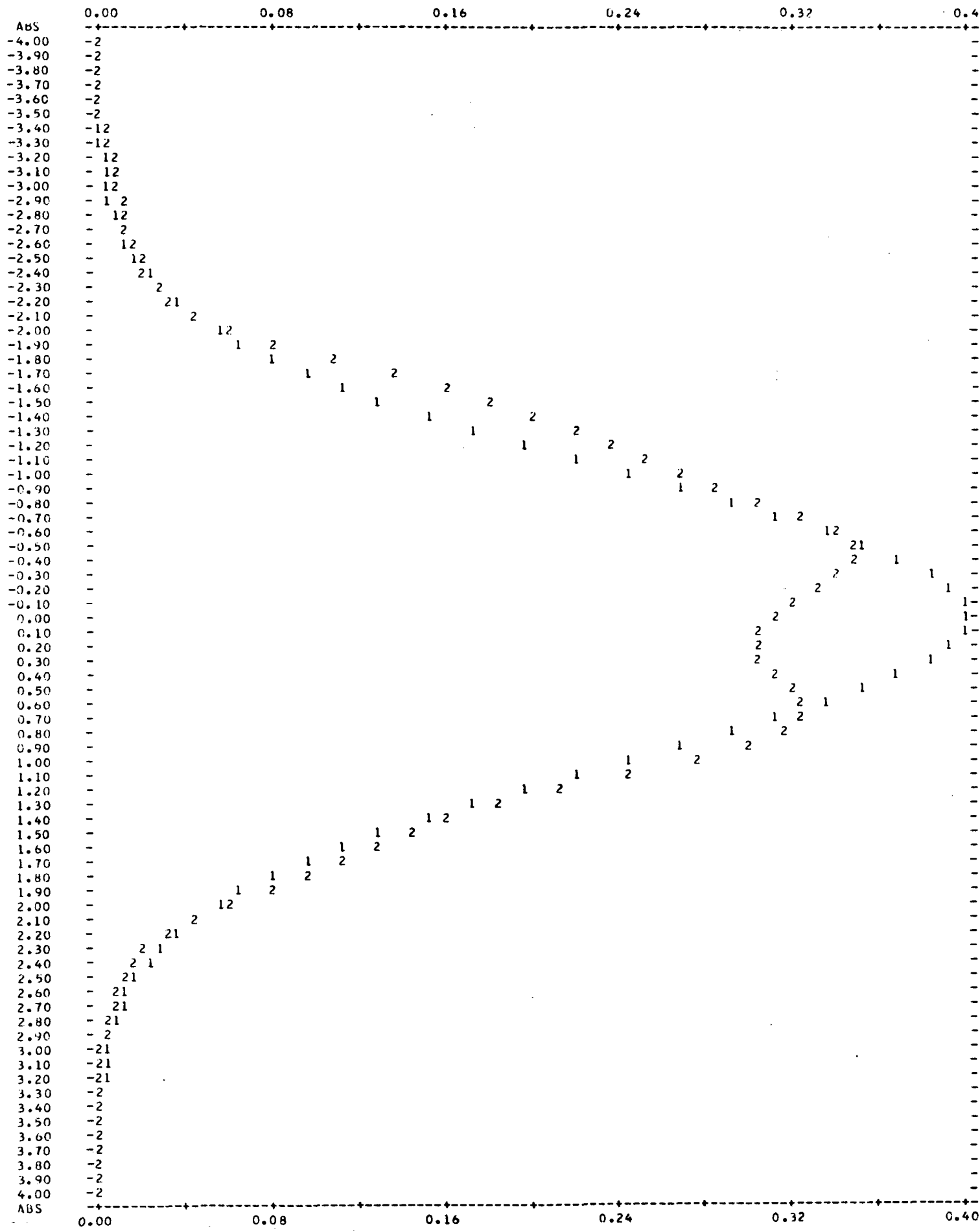


PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE N(0,1) , 2 DENOTES ESTIMATED  
 N = 100 S = 0.07



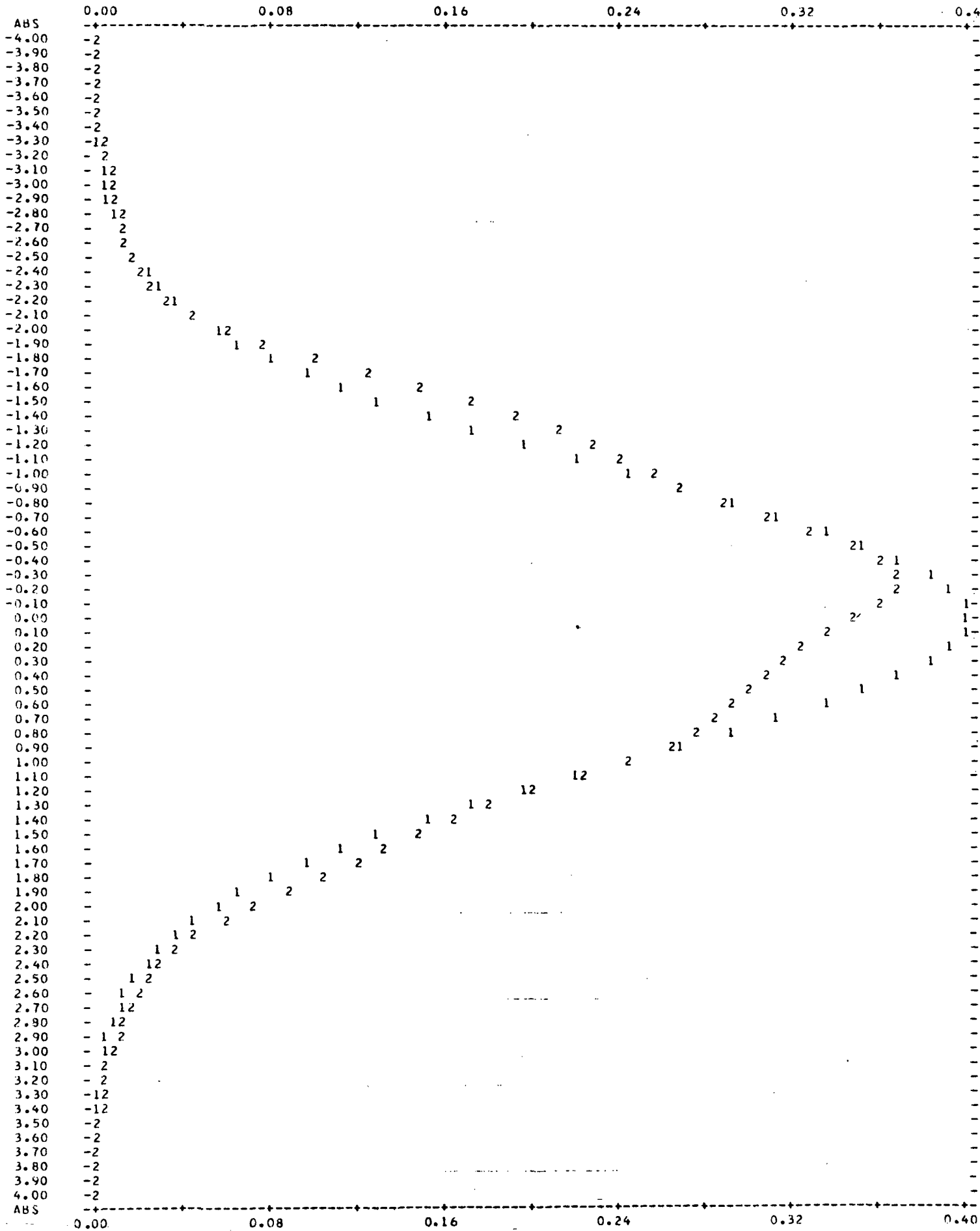
GRAPH 12

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE N(0,1) , 2 DENOTES ESTIMATED  
 N = 200 S = 0.07



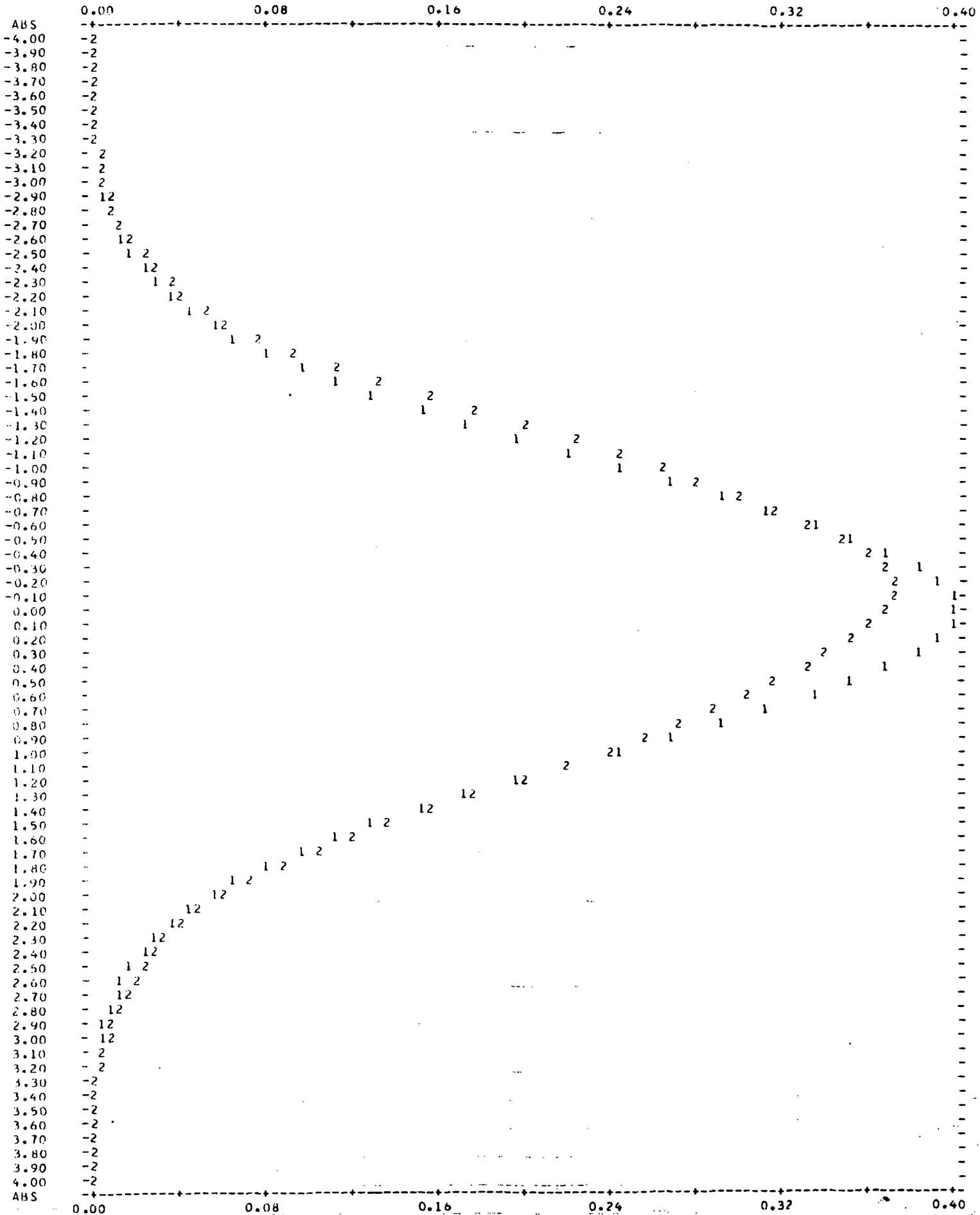
GRAPH 13

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $N(0,1)$ , 2 DENOTES ESTIMATED  
 $N = 500$   $S = 0.07$

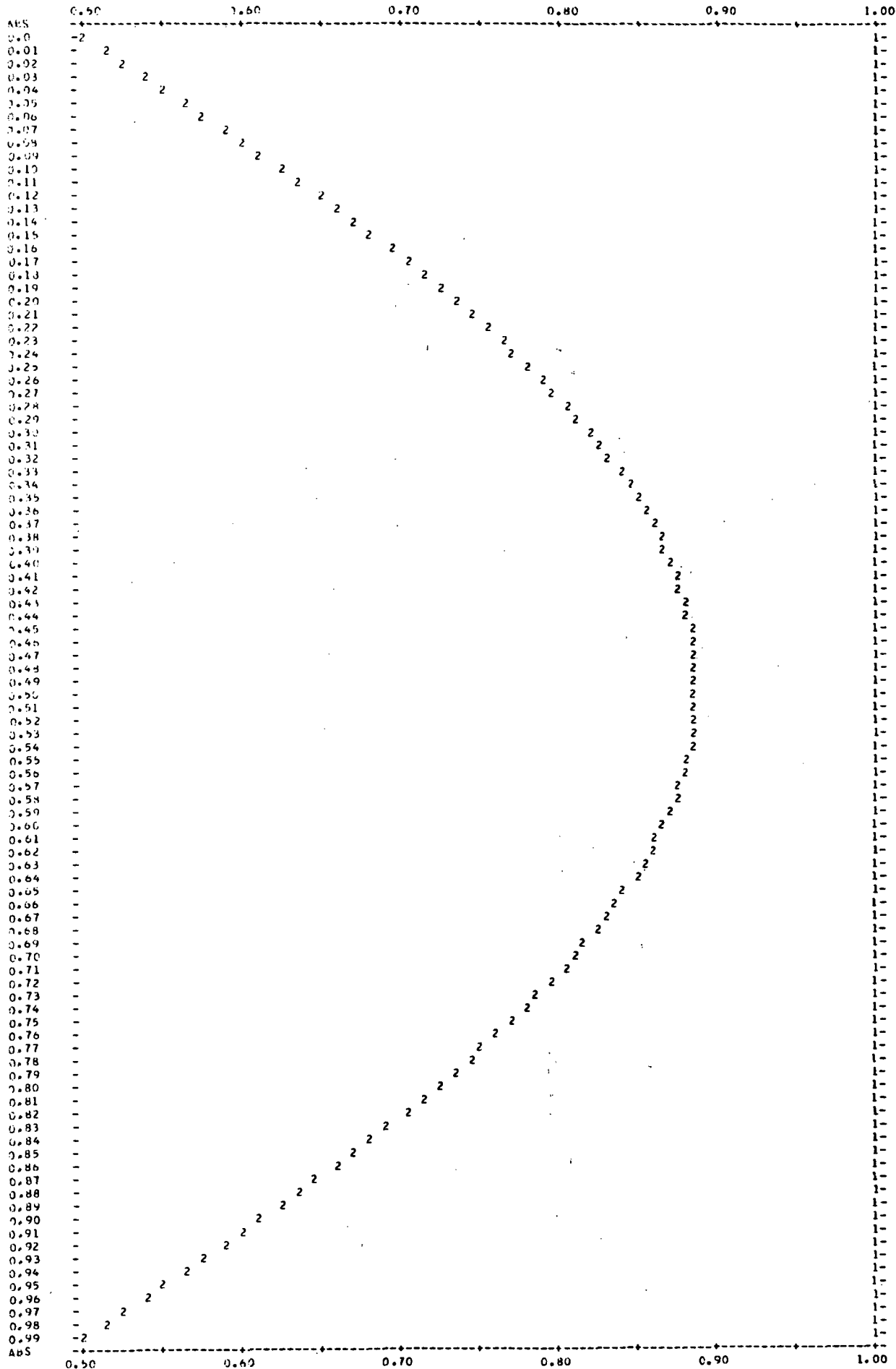


GRAPH 14

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $N(0,1)$ , 2 DENOTES ESTIMATED  
 $N = 1000$   $S = 0.07$



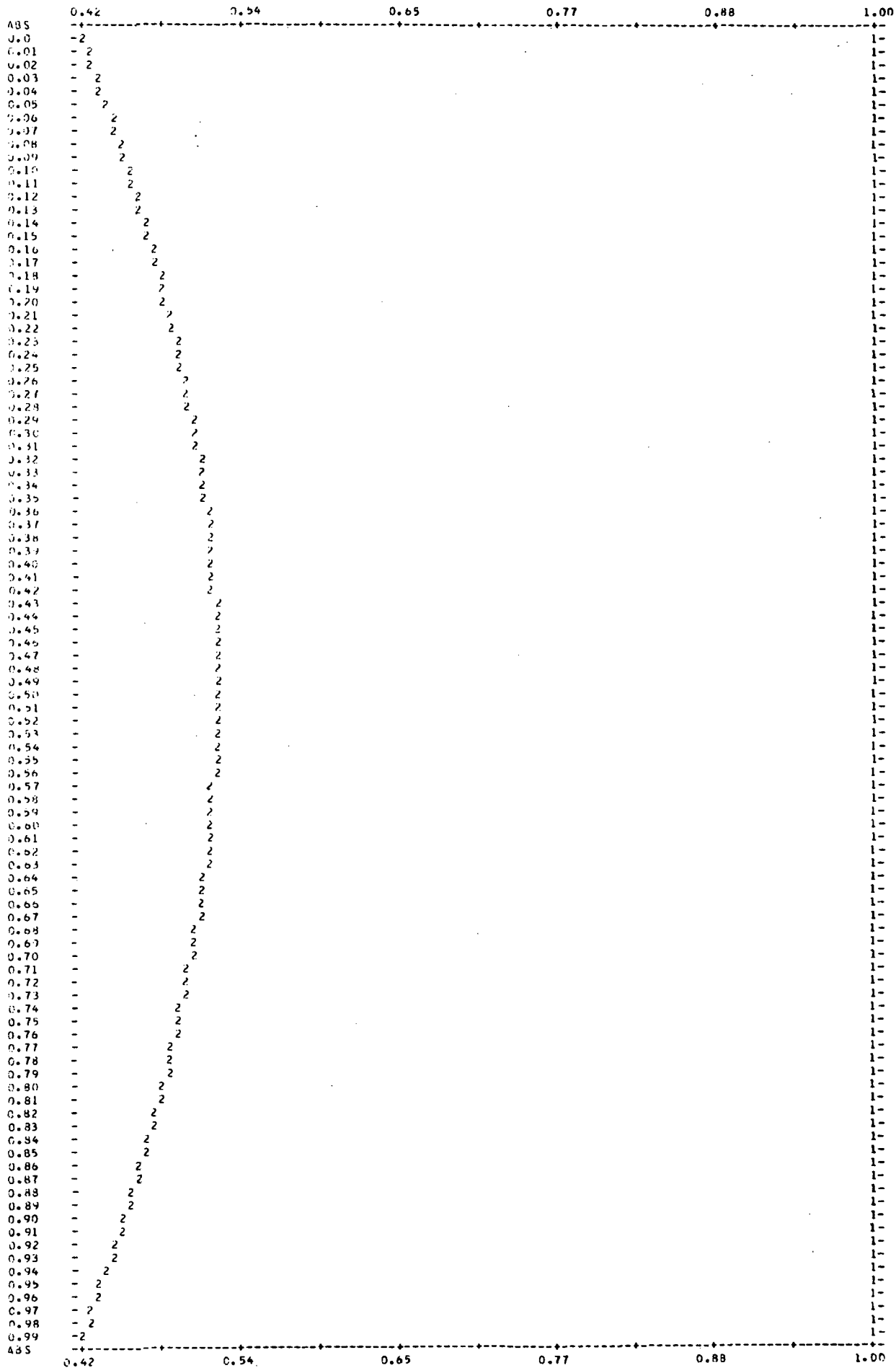
**Graph 15**  
 PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE U(0,1) , 2 DENOTES ESTIMATED  
 N = 7000 S = 0.10



IX = 204186593

THE MAXIMUM ABSOLUTE VALUE OF THE DIFFERENCES OF FN AND FNX IS 0.495 FOR N = 7000

**Graph 16**  
 PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE U(0,1) ; 2 DENOTES ESTIMATED  
 N = 7000 S = 0.50



IX = 204186593

THE MAXIMUM ABSOLUTE VALUE OF THE DIFFERENCES OF FN AND FN\* IS 0.496 FOR N = 7000



# Graph 17

PLOTS OF TRUE AND ESTIMATED DENSITY FUNCTIONS  
 1 DENOTES TRUE  $J(x,1)$ , 2 DENOTES ESTIMATED  
 N = 7000 S = 0.09

