

ARTIFICIAL INTELLIGENCE
IN STATISTICS

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Abstract

More intelligent statistical software is urgently needed. Of equal importance is that responsible statisticians be intimately involved in the process of developing such software and not abdicate this responsibility to, e.g., the AI community. A summary of some recent and current work is presented here.

1 Introduction

The title of this paper refers to what is commonly called “more intelligent” statistical software: in other words, statistical software which embodies features developed in the realm of Artificial Intelligence, most notably the *expert system*. The title should not be confused with “Statistics in Artificial Intelligence” which has to do with the problem of handling so-called “uncertain knowledge” in all kinds of expert systems. Both topics get equal time in Gale (1986), but only one will be discussed here.

However, there is, in Statistics in AI, an important object lesson to which I want to allude before getting back on track. AI people have apparently largely turned their backs on real probability (e.g. Bayes’ formula), preferring instead such incoherencies as Belief Functions, Certainty Measures, and Fuzzy Sets. “Bayesian ideas don’t work,” you may hear them say, when in fact they haven’t been properly tried at all. Actually, Bayesian ideas *do* work; a good example is Spiegelhalter (1984). But statisticians haven’t paid enough attention to the problem, hence these other techniques have largely filled a vacuum. It is vitally important that responsible statisticians not allow the same thing to happen in the development of the statistical software of the future.

*Based on a lecture October 4, 1988 at the National Institute of Standards and Technology, Gaithersburg, MD.

2 Quotable Quotes

Here is how one particularly celebrated observer, John Tukey, assessed the magnitude of the subject in 1985, in quotes taken from Gale (1986):

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To many people, the “They” in Tukey’s quote are some kind of expert systems, which prompts this cautious appraisal from Peter Huber (1985), also in Gale (1986):

... There are no real experts for data analysis, *per se*. Thus an essential ingredient for building an expert system for exploratory data analysis is lacking.

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We’ll give the last word to Tukey, although he said it in 1982:

[the] all-too-automatic reaction by many statisticians and data analysts, the reaction that automating... is a threat to their professional position... is a serious misconception.

3 Paradigms

What kind of intelligence should statistical software have, and where should this intelligence come from? Here are two quite different approaches, the first essentially due to Huber, the second to Gale, among others.

3.1 The Lab Assistant

As Figure 3.1 suggests, a scientist has come to a real-live data analyst for help, which is being provided *in real-time!* This allows for *interaction* between them. Either one can suggest approaches and react and adapt to the results. This is, of course, vastly superior to the old-fashioned batch mode approach. But, for it to actually be feasible requires software that is more than merely “interactive.” As Huber suggests, it should be responsive to the System Experts wishes in much the same way as a graduate lab assistant would be (but *much faster!!*).

“Check the correctness of these model assumptions [perhaps by doing some simulations],” we should be able to say to our software. Or “repeat the analysis we just did with this modified data;” or “modify the analysis with the same data, as follows...” Needless to say, the software would do our bidding unobtrusively, allowing us to simultaneously pursue other tasks, and politely prompt us when it’s ready to show off its results. Meanwhile, our electronic lab assistant would be keeping a diary of our session—but not a passive, recording device type of diary such as currently exists in some statistical packages. This diary is to be a lot like a lab assistant’s notebook. For example, the users might see on the screen a message like: “excuse me, but would you like to comment on the fit?” and the comments would become diary annotations. The diary might also contain things which are done in the background, without the users’ explicit knowledge, but which the software “thinks” will be needed later.

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3.2 The Compleat Consultant

As Figure 3.2 shows, the Data Analyst now switches seats and plays a role analogous to the Scientist in the previous paradigm, providing expertise about his own specialty, Statistics. An example of this collaboration occurred at Bell Labs where Bill Gale played the role of

PARADIGM : THE LAB ASSISTANT

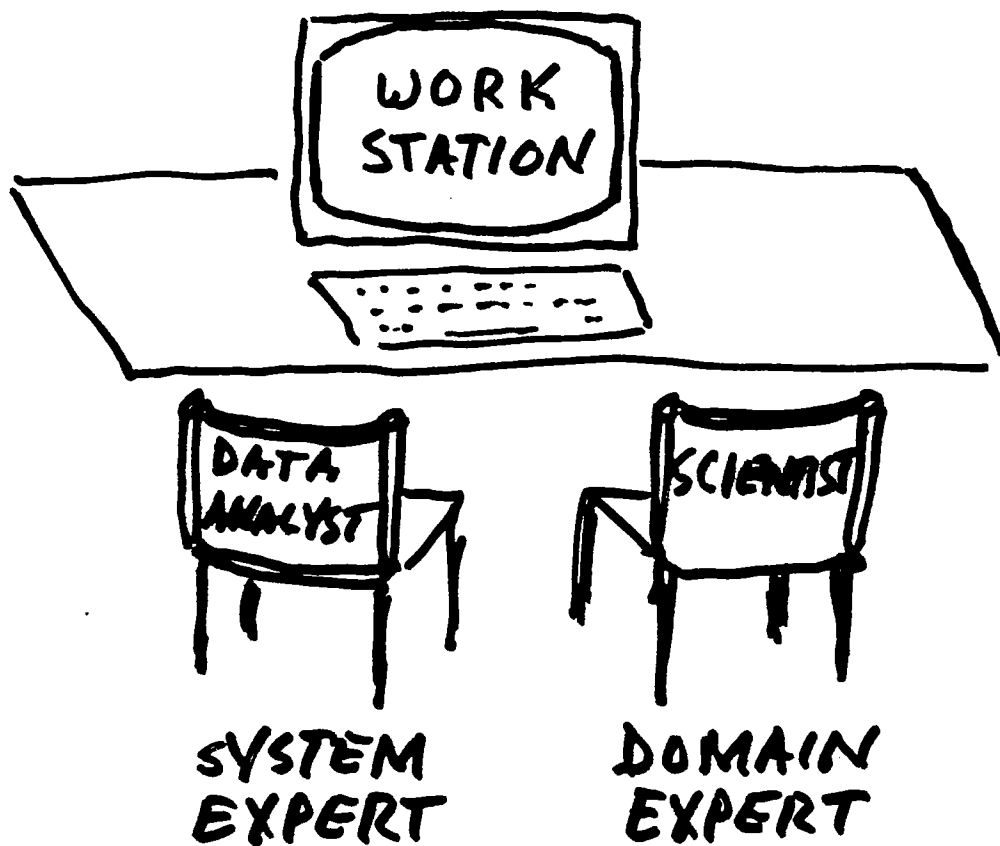


Fig. 3.1

PARADIGM : THE COMPLETE CONSULTANT

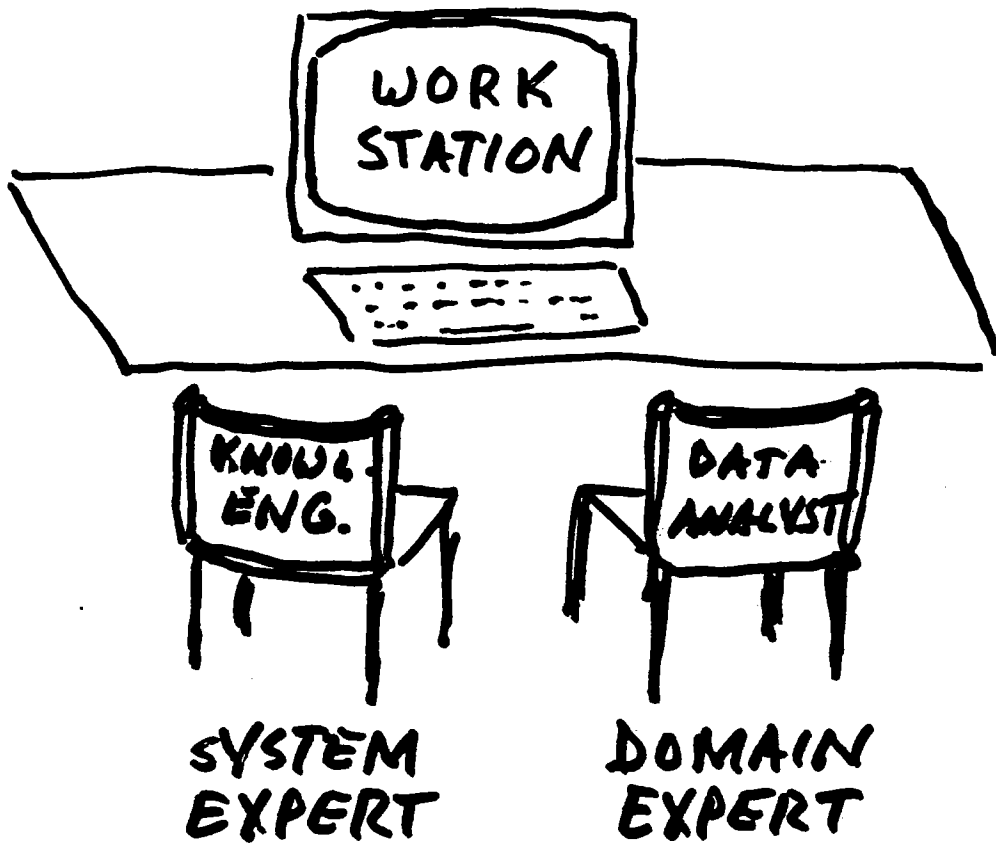


Fig. 3.2

Knowledge Engineer and Daryl Pregibon was the Data Analyst. The program they created was REX (Regression Expert); it's mentioned in the next section.

The object here is much more ambitious, to create a statistical expert system, which can then be used by statistical laypersons like the scientist, rather than by professional statisticians. How else can we do what Tukey said needs to be done?

3.3 Two goals...or one?

But notice that Tukey spoke not only of *improving* but also of *understanding* data-analytic systems. So while we are striving to automate data analysis by building expert systems, we need to be keenly aware of the need for some kind of a theory to help us understand what is really "significant" among the multitude of things which computing power allows us to see. It is interesting to note that both of these goals require us to formalize the process of data analysis, or as some have said, to try to "capture statistical strategy."

4 Prototypes

Most of the examples to follow were presented at Compstat VIII, a Symposium held in Copenhagen in August, 1988 under the auspices of the International Association for Statistical Computing. Almost without exception, the word "prototypes" is much too optimistic; most never have and never will be put into production, or even be seriously used by anyone other than their developers.

REX Regression EXpert. Developed by Gale and Pregibon at AT&T Bell Labs. The goal was to encode enough expert knowledge to enable a novice user to do a simple linear regression "safely." See Figures 4.1 and 4.2 for illustrations of the multi-window environment it provides the user.

STUDENT Learn how to do data analysis by studying examples, such as diaries of sessions with live experts.

TESS (Tree-based Environment for Statistical Strategies) Here Gale and Pregibon abandoned trying to model a human analyst, in part because they became convinced that only a human can supply enough of the *context*. Alternatively they now seek context-free results (note the plural). Their inspiration is the classic book of Daniel and Wood (1971, 1980), who said

Although we usually get our notions one at a time, it does not follow that we will find the best equation(s) by accepting or rejecting each notion after examining it *once*. It will often be possible to broaden our experience by looking at each new idea in the full context of its predecessors.

We are considering whether we can regress brain.y on brain.x
 But first, The distribution of y is unduly skew
 skewness of y is quite large.
 Using the rule:

DIALOGUE

if The distribution of y is unduly skew
 then assert that logarithms of The response variable y should be used
 and the rule
 if sign of y is positive
 then assert that logarithms of The response variable y should be used
 We suggest the fix
 that logarithms of The response variable y should be used
 (Type 'c' to continue)

missing data test : ok
 granularity of y : ok
 spacing of y : ok
 skewness of y : severe

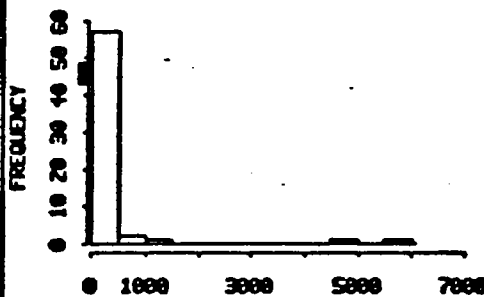
The vertical scale shows the number of points in the interval of values shown on the horizontal scale. The histogram of the transformed variable should be more evenly distributed.

**INTERP.
 OF
 TESTS**

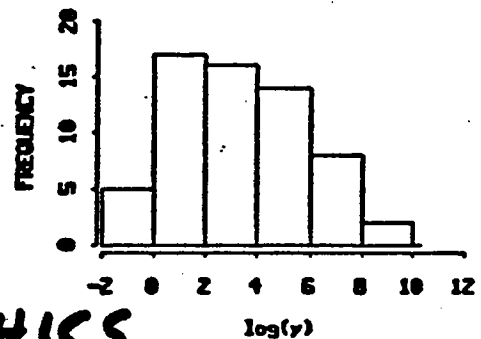
**TRACE
 INFO**

BEFORE AND AFTER HISTOGRAMS

HISTOGRAM OF y



HISTOGRAM OF log(y)



GRAPHICS

13:20 0.92 +0.42

4.7
 Figure 8.10

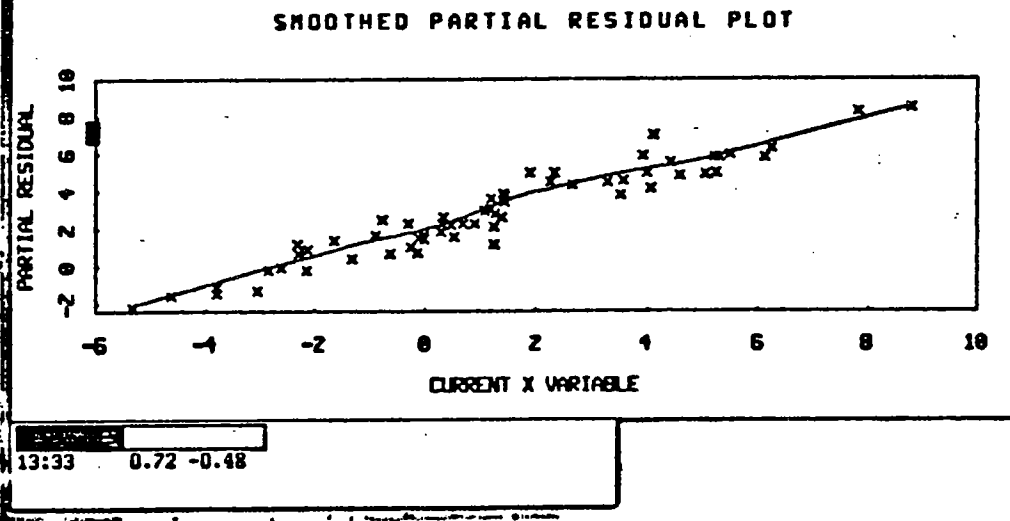
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```
This plot has overlays.  
EXIT ON: resume.analysis  
You might want to see:  
least squares line  
>
```

```
extremes of x : ok  
■
```

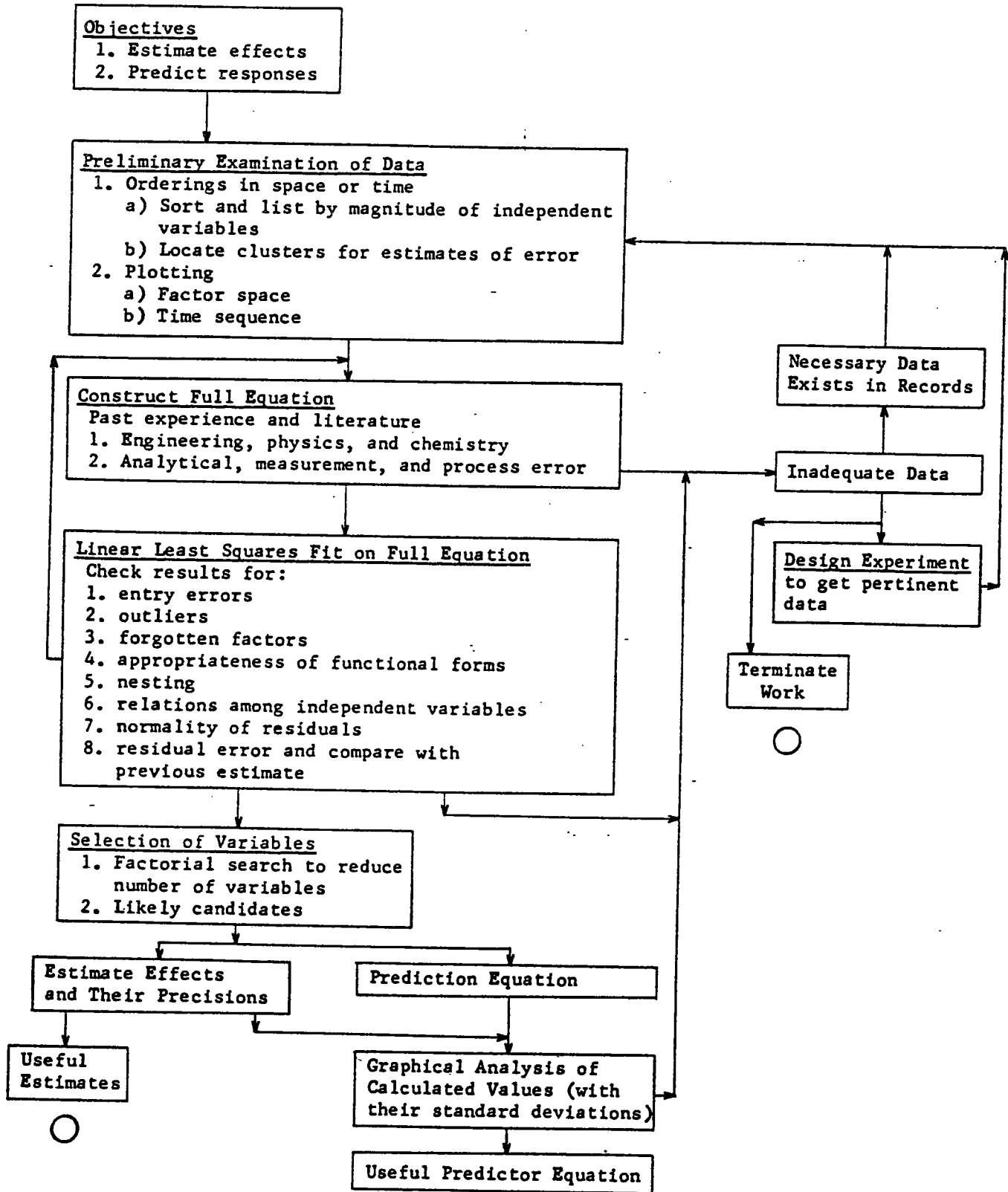
```
offset)  
We are now beginning a master frame named undomark  
We are now beginning a choice frame named xatypical  
We are now beginning a test frame named xextremes  
Calling S with ?extremes(x)  
The suggestion that The distribution of The current x has  
atypical values is not supported.  
We are now beginning a master frame named undomark  
We are now beginning a choice frame named linearity  
Calling S with ?reginitial  
We are now beginning a test frame named smoothtest  
Calling S with ?smoothtest  
Calling S with ?smoothplot  
■
```



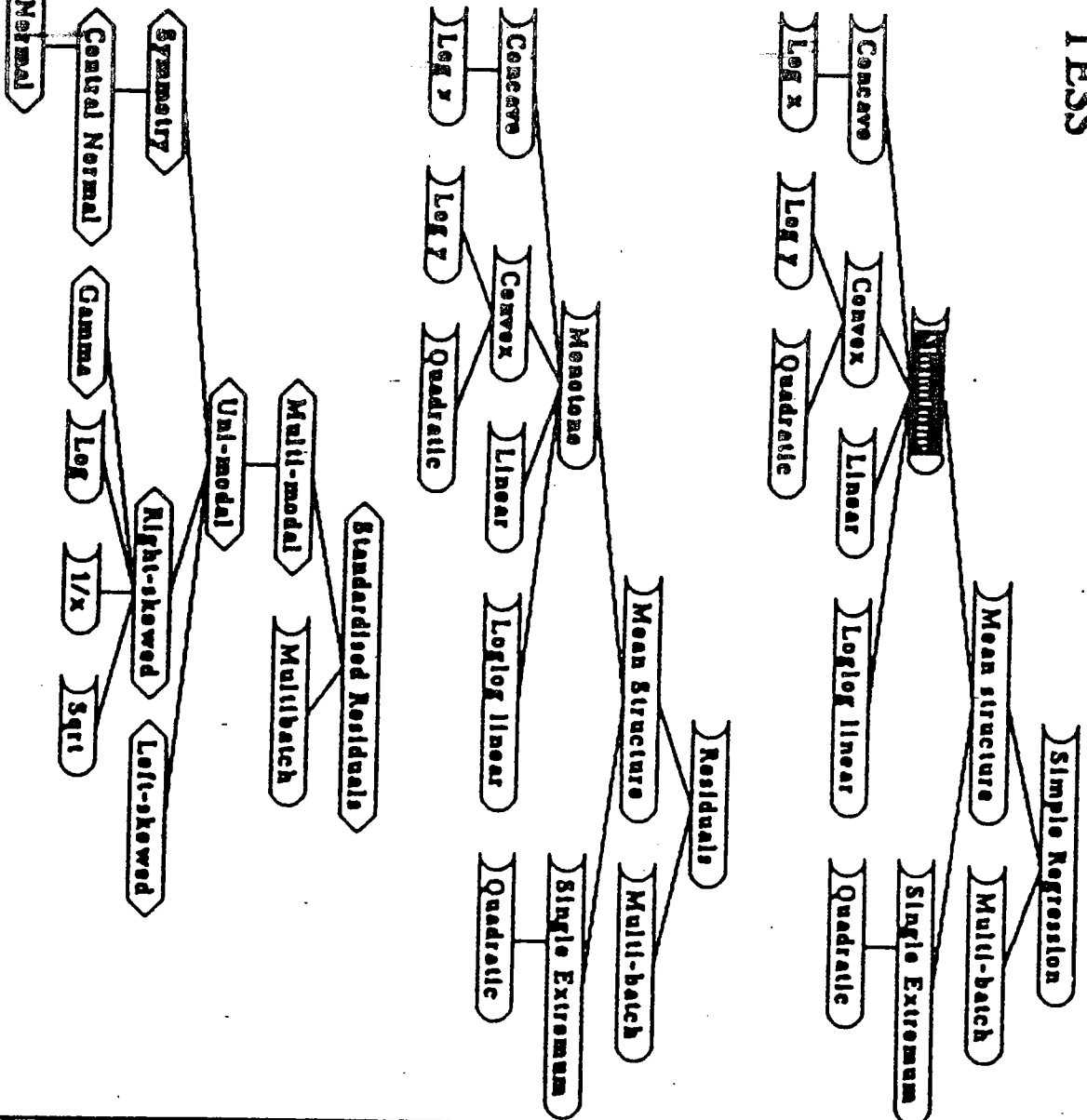
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Figure 8.12 We accepted the logarithmic transform suggested for the dependent variable. REX made a few more tests on the transformed dependent variable, then considered the independent variable. The same kind of skewness problem was found, and a logarithmic transform made there also.

The next stage of the analysis is linearity checking. The test used finds a mild nonlinearity, so REX pauses to ask if the user wants to call the problem ok. A plot is offered, which we accept. The plot show a scatter plot of the transformed variable and a smoothing curve. The curve shows a small bump in the middle. We would suggest calling this "ok." In fact, REX does not have a means of fixing this problem.

FITTING EQUATIONS TO DATA



4.3
 Figure 1.1 Flow diagram for fitting equations to data.

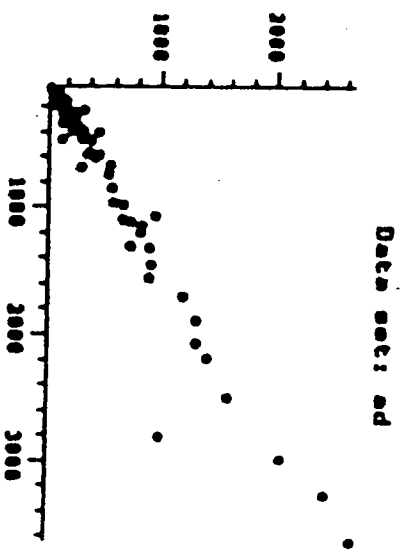


Current tree: BLR
 Current data set: ad

Enter values for Transform node:
 Node label : Monotone
 Transformation : monotone(x)
 Send new dataset : monotone(x)
 Pre Conditions : len(xof(x)) > 20
 Transform Description : Residuals from monotone smooth
 Arguments : d
 Test : monotonicity(x)
 Test Description: ~\N evidence of monotonicity
 Arguments : d
 Plot Title :
 Plot expressions: test\Monotone(x)

Add a Data Set
 Calibrate Node
 Change Font
 Current Data Set
 Delete Current Data Set
 View Trees
 Reset Root
 Start New Tree
 Test Node

Batch Describe
 Calibrate Tree
 Check Consistency
 Detach
 Describe
 Plots
 Save State
 Test All Data Sets



Leap Listener Pane 1

Fig 4.14
 Fig. 2. Screen image of TESS in the basic mode of interaction.

The flow chart from their book (Figure 4.3) inspired the tree structure in Figure 4.4. A central idea in TESS is the trade-off between *accuracy* and *parsimony*, the measurement of which is not yet fully worked-out.

RX Translates medical problems into statistical problems, and does regression.

MUSE (Method to USE) Selects appropriate method of analysis based on user-supplied inputs and outputs.

DINDE (“turkey” in French; don’t ask why.) The work of Oldfield and Peters in the US. Object oriented: “provides a visual map of an analysis.” For use by experts.

CADEMO Computer-Assisted Design of Experiments and MOdelling. A large consortium of East Germans is producing this.

SELINA another experimental design support system, developed in the UK.

PRINCE front-end for PRINCALS (PRINcipal Components AnaLysiS), developed in the Netherlands

GLIMPSE front-end for GLIM (Generalized LLinear Models), developed by Nelder et al in the UK.

5 Questions and Answers

There is currently considerable debate centering on questions such as

- WHO is it for? At the present stage of development, should we primarily trying to help the professional data analyst, as in the first paradigm, or should be aiming directly at the novice? It is not too much of an oversimplification to summarize the sentiment at Compstat 88 by saying that the Americans seemed to have scaled back their ambitions from the latter toward the former, while the Europeans are concentrating—but not very ambitiously—on the latter.
- WHAT should it do? Should it do several kinds of data analysis, or just one kind; or should it be oriented toward a particular kind of application rather than toward a particular kind of Statistical technique.
- WHY do we need it?

Here is the moral imperative: Statistical software in its present form, made widely available by cheap computing, will precipitate much uninformed, unguided, and simply incorrect data analysis. We are obliged to do something to help.

–Chambers (1981)

References

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- [4] Spiegelhalter, D. J., and Knill-Jones, R. P. (1984) Statistical and knowledge-based approaches to clinical decision-support systems, with an application to gastroenterology (with discussion). *J. Royal Statistical Society, Series B* **147** 35–77.

STATISTICAL ANALYSIS FOR
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WITH APPLICATIONS TO
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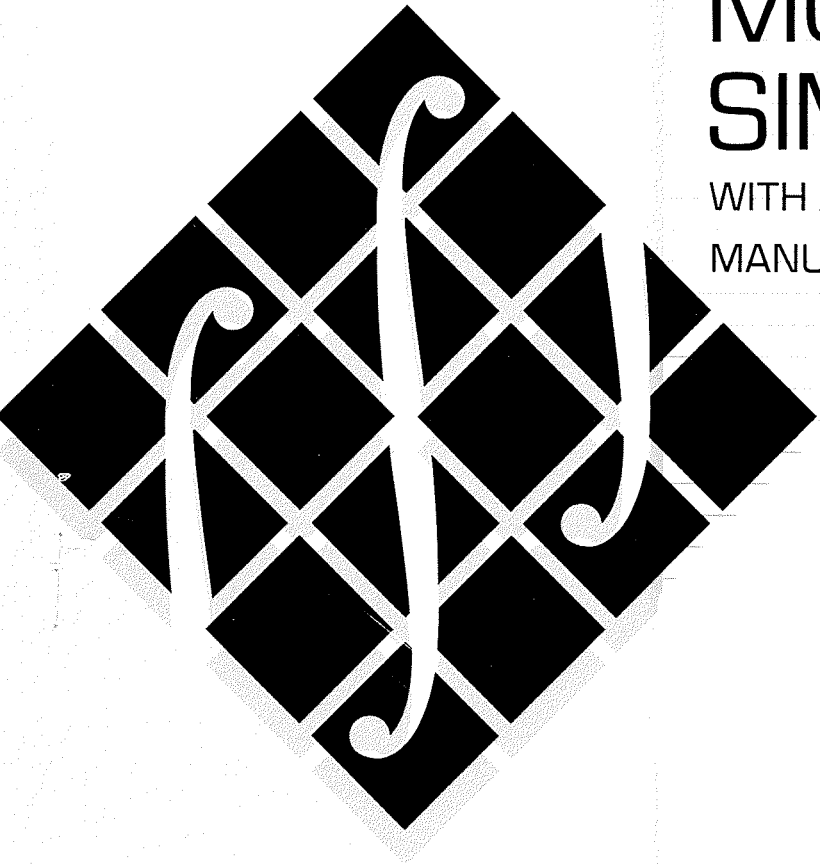
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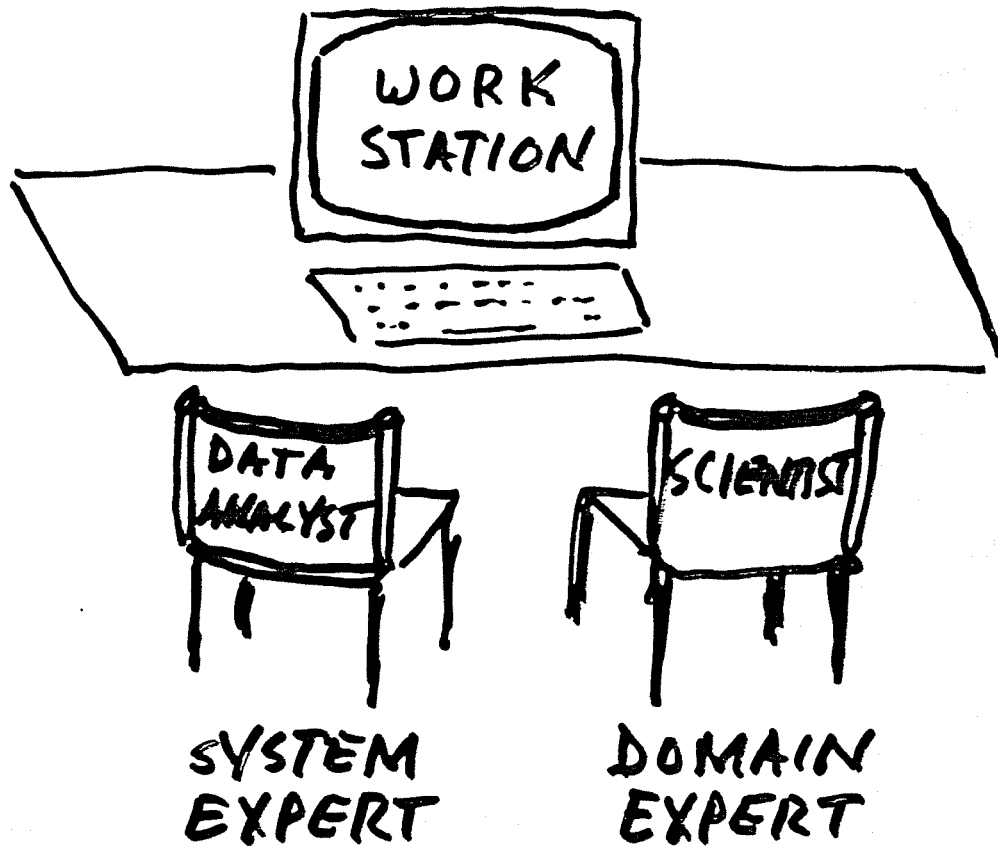


Fig. 3.1

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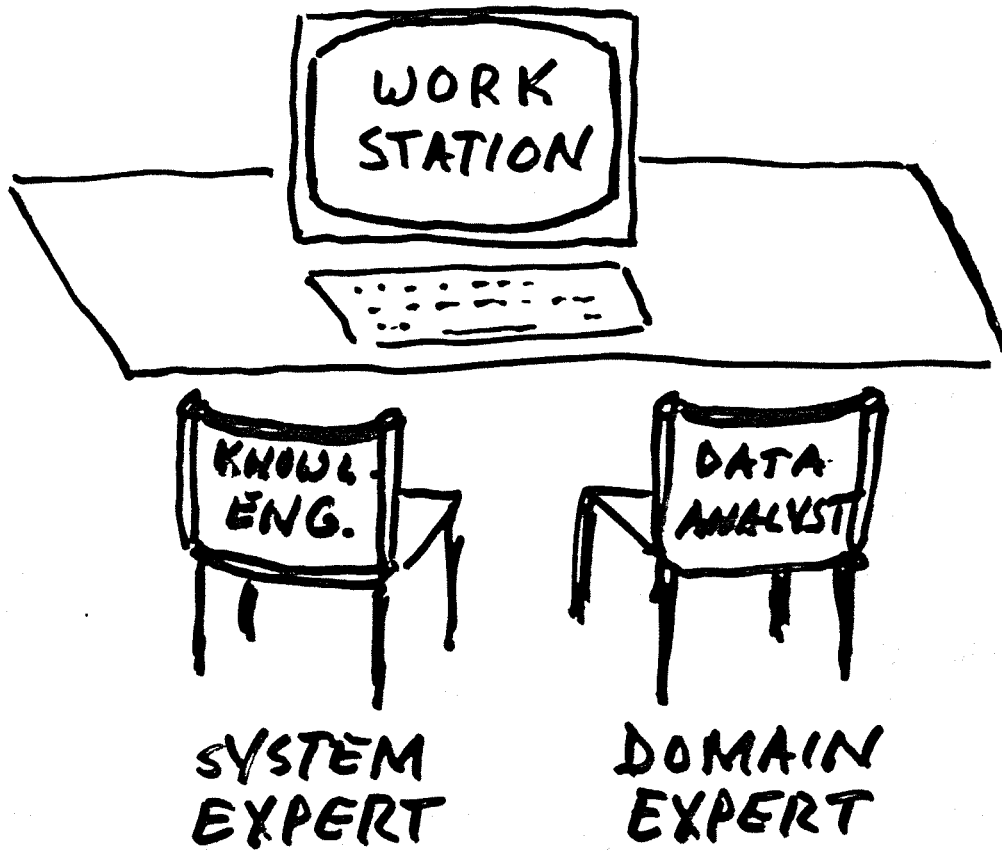


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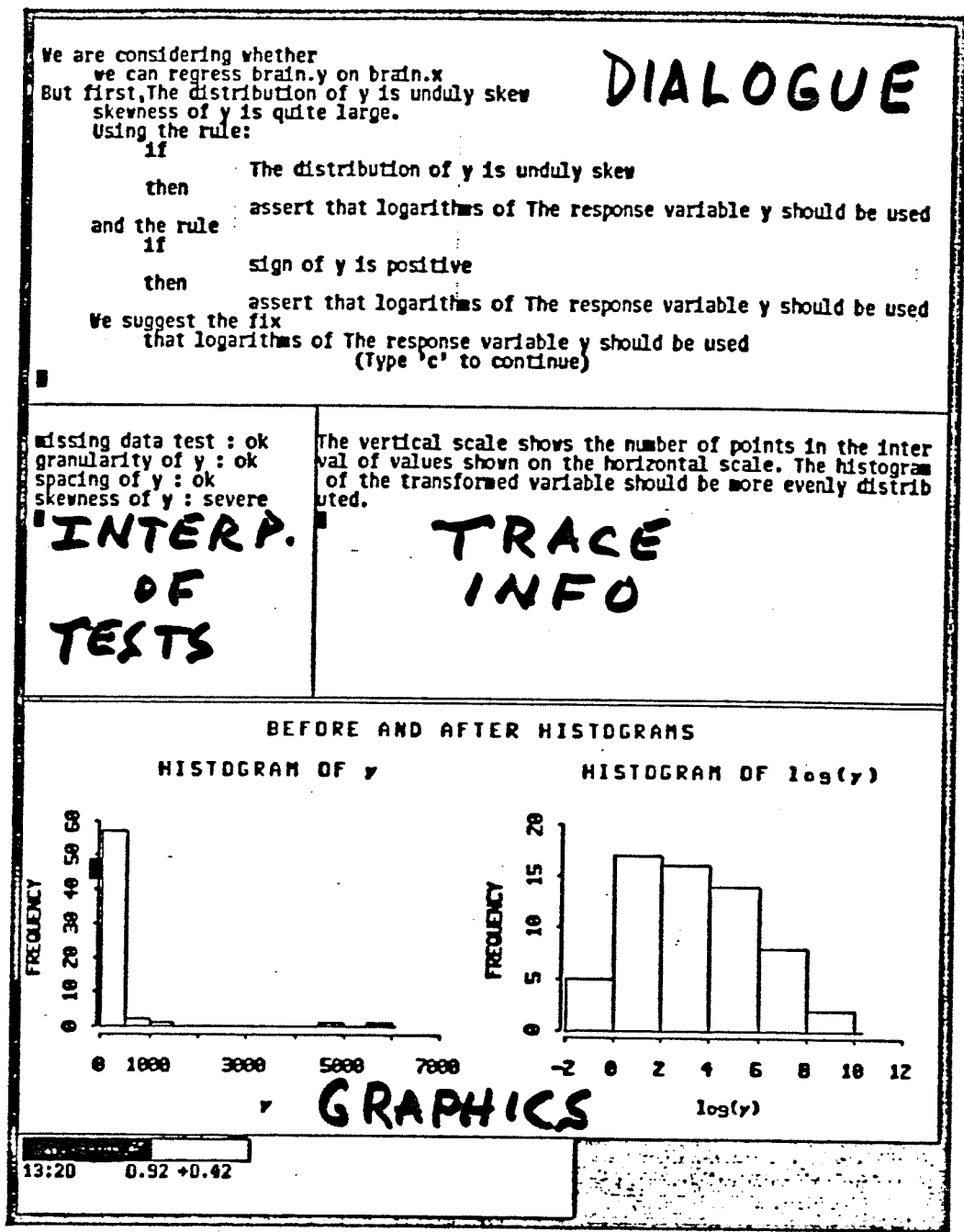
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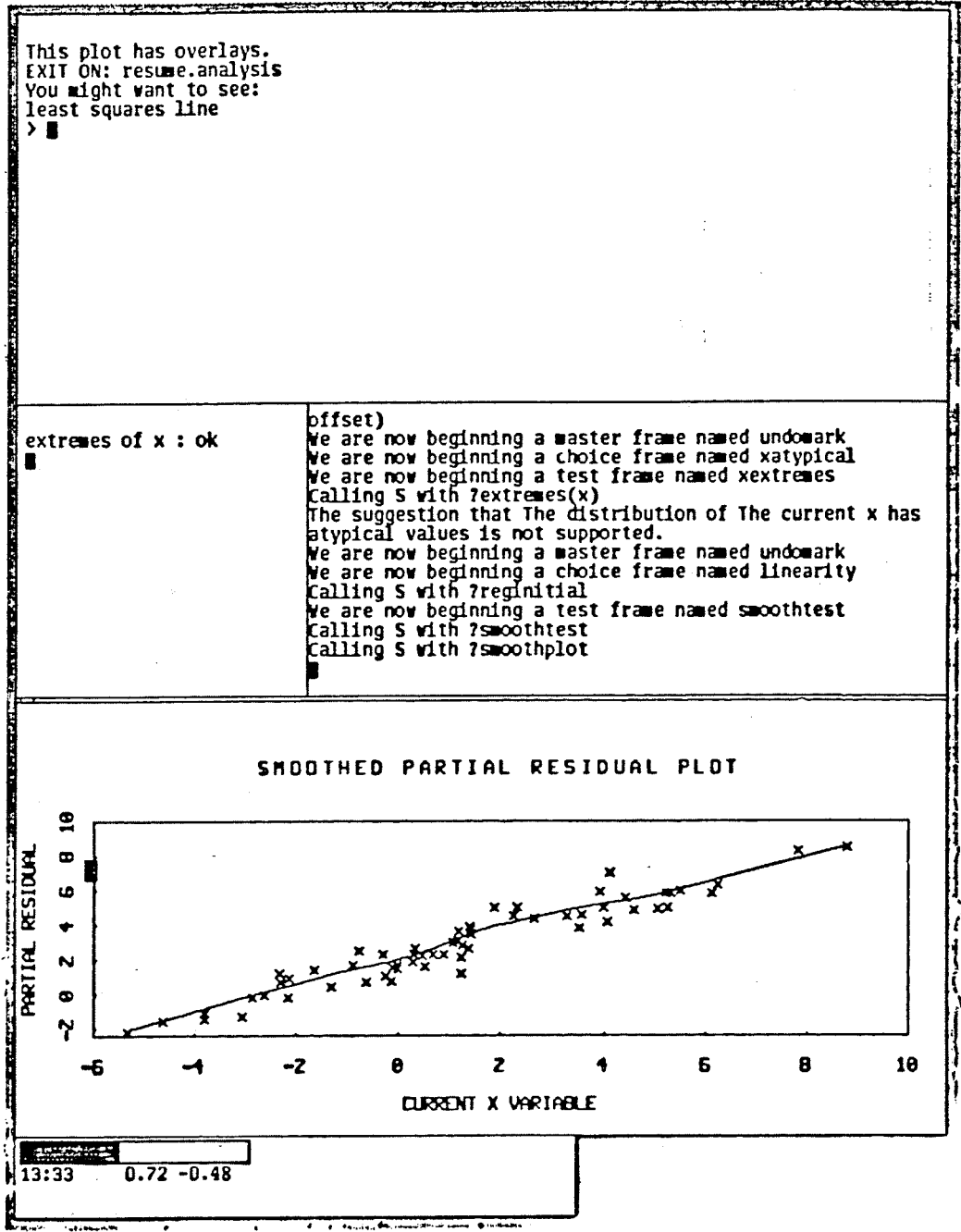
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4.7

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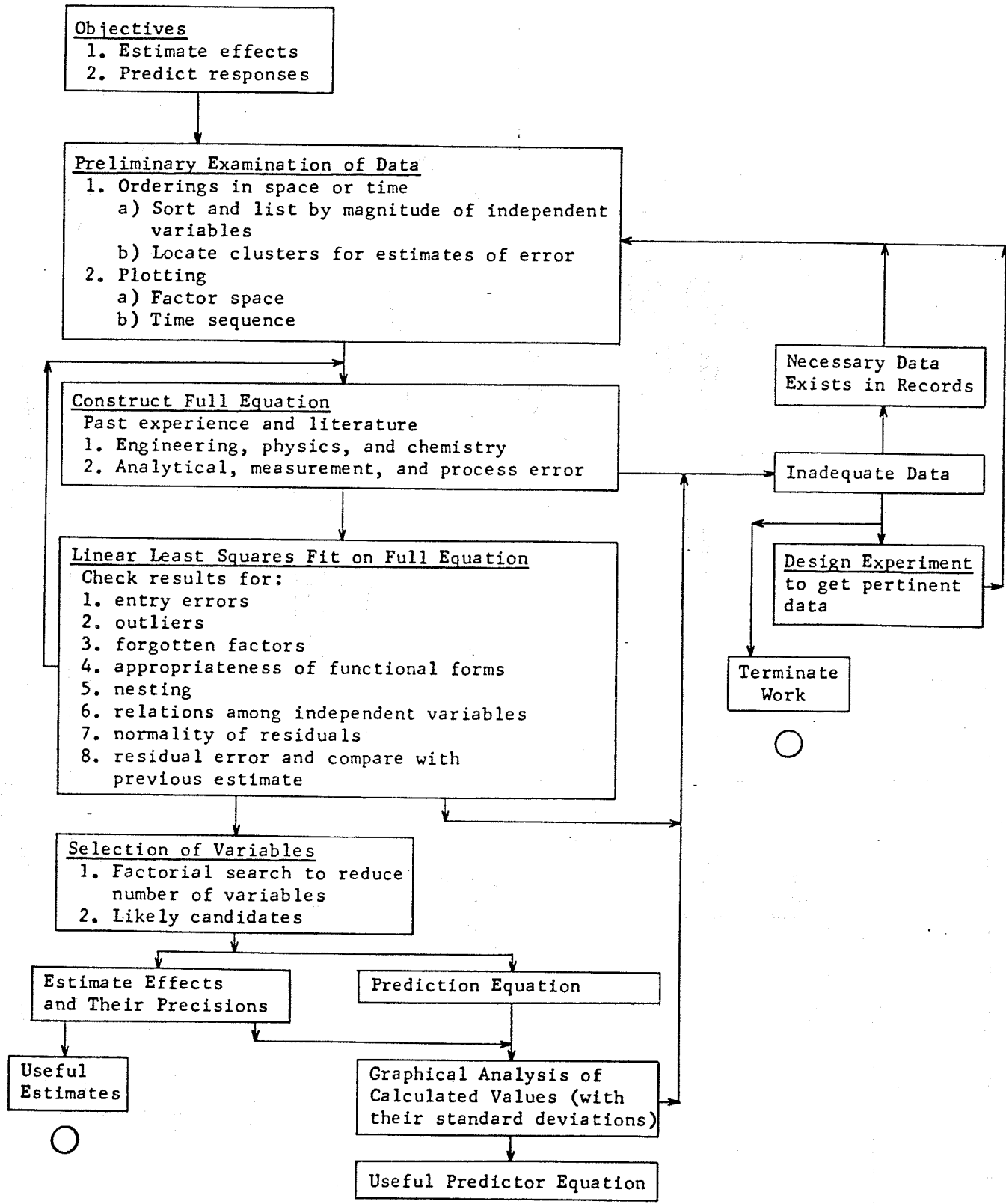
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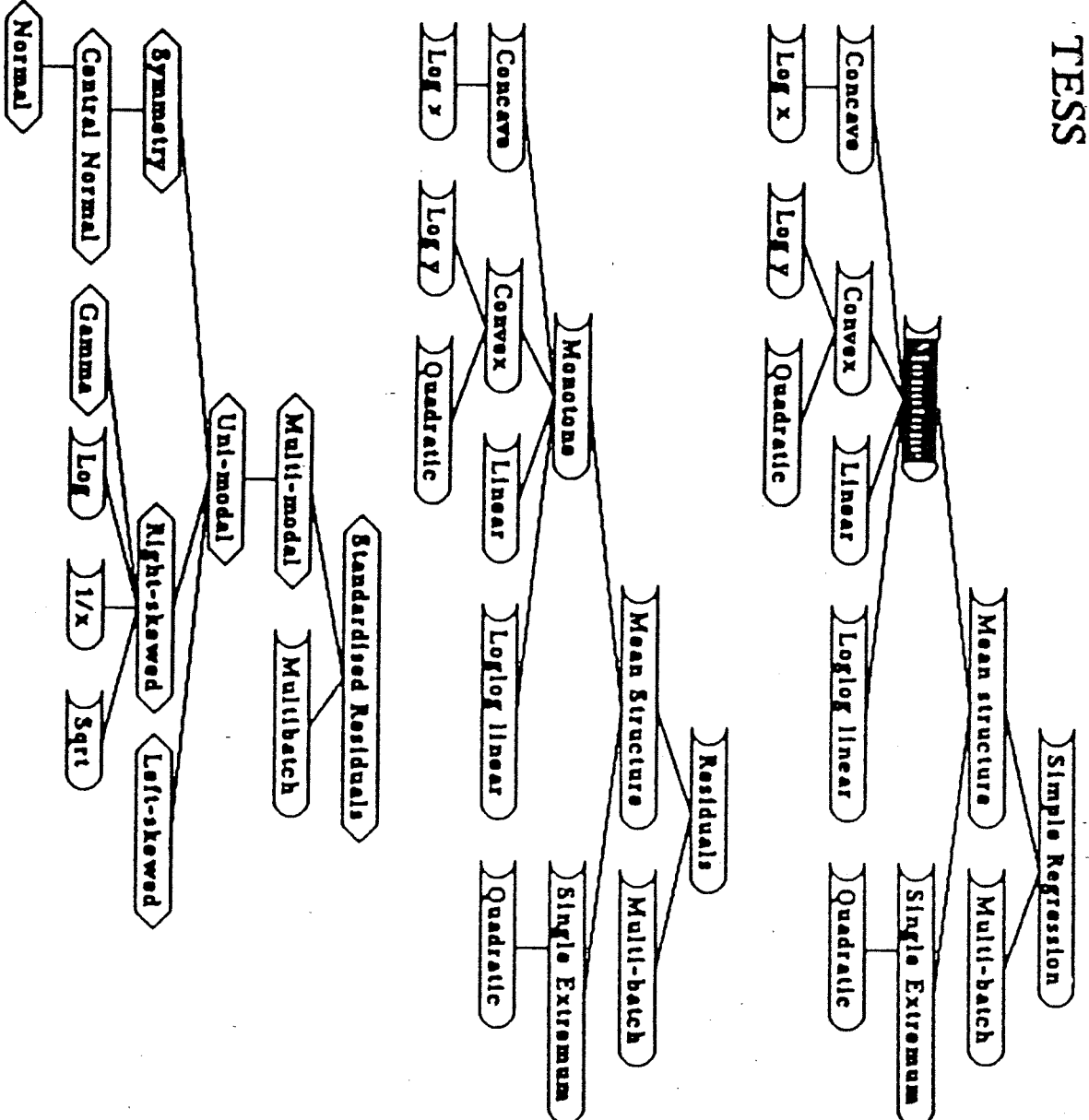
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FITTING EQUATIONS TO DATA



43
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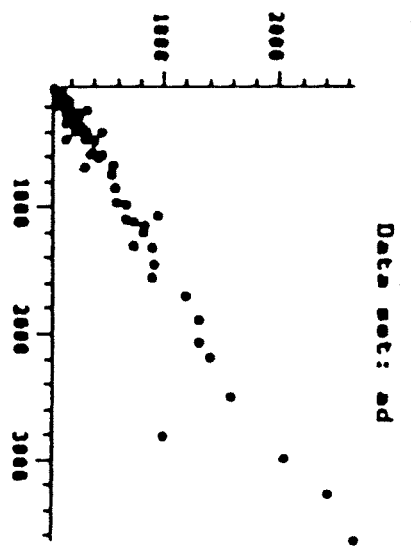
Tree Pane 1 Current tree: BLR Current data set: ad

Top

Enter values for Transform node:
 Node label : Monotone
 Transformation : monores(x)
 Send new dataset : R:Residuals
 Pre Conditions : len(xof(x)) > 20
 Transform Description : Residuals from monotone smooth
 Arguments : d
 Test : monotonicity(x)
 Test Description: ~\VA evidence of monotonicity
 Arguments : d
 Plot Title :
 Plot expressions: test\Monotone(x)

Bottom

- Add a Data Set
- Calibrate Node
- Change Font
- Current Data Set
- Delete Current Data Set
- View Trees
- Reset Root
- Start New Tree
- Test Node
- Batch Describe
- Calibrate Tree
- Check Consistency
- Detach
- Describe Plots
- Save State
- Test All Data Sets



Lisp Listener Pane 1

Fig 4.14
 Fig. 2. Screen image of TESS in the basic mode of interaction.

The flow chart from their book (Figure 4.3) inspired the tree structure in Figure 4.4. A central idea in TESS is the trade-off between *accuracy* and *parsimony*, the measurement of which is not yet fully worked-out.

RX Translates medical problems into statistical problems, and does regression.

MUSE (Method to USE) Selects appropriate method of analysis based on user-supplied inputs and outputs.

DINDE (“turkey” in French; don’t ask why.) The work of Oldfield and Peters in the US. Object oriented: “provides a visual map of an analysis.” For use by experts.

CADEMO Computer-Assisted Design of Experiments and MOdelling. A large consortium of East Germans is producing this.

SELINA another experimental design support system, developed in the UK.

PRINCE front-end for PRINCALS (PRINCipal Components AnaLysiS), developed in the Netherlands

GLIMPSE front-end for GLIM (Generalized LInear Models), developed by Nelder et al in the UK.

5 Questions and Answers

There is currently considerable debate centering on questions such as

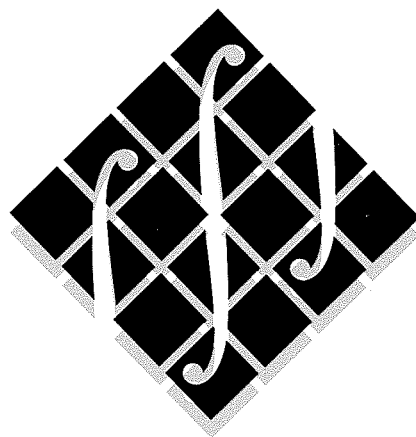
- WHO is it for? At the present stage of development, should we primarily trying to help the professional data analyst, as in the first paradigm, or should be aiming directly at the novice? It is not too much of an oversimplification to summarize the sentiment at Compstat 88 by saying that the Americans seemed to have scaled back their ambitions from the latter toward the former, while the Europeans are concentrating—but not very ambitiously—on the latter.
- WHAT should it do? Should it do several kinds of data analysis, or just one kind; or should it be oriented toward a particular kind of application rather than toward a particular kind of Statistical technique.
- WHY do we need it?

Here is the moral imperative: Statistical software in its present form, made widely available by cheap computing, will precipitate much uninformed, unguided, and simply incorrect data analysis. We are obliged to do something to help.

—Chambers (1981)

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STATISTICAL ANALYSIS FOR

STOCHASTIC MODELING and SIMULATION

WITH APPLICATIONS TO MANUFACTURING