

# Response to Jon Bentley's “Little Experiments on Algorithms”

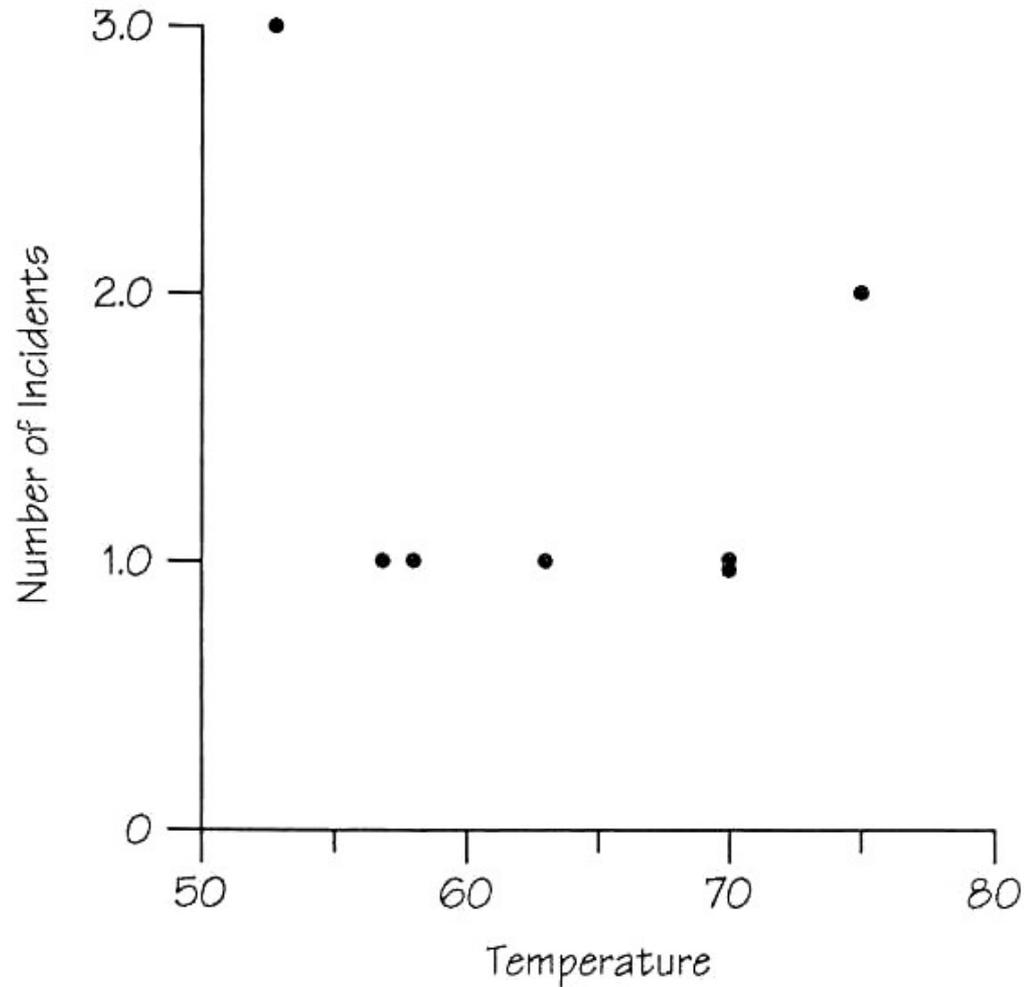
Jim Landwehr  
(with input from Colin Mallows and Jean Meloche)

Data Analysis Research Dept.  
Avaya Labs  
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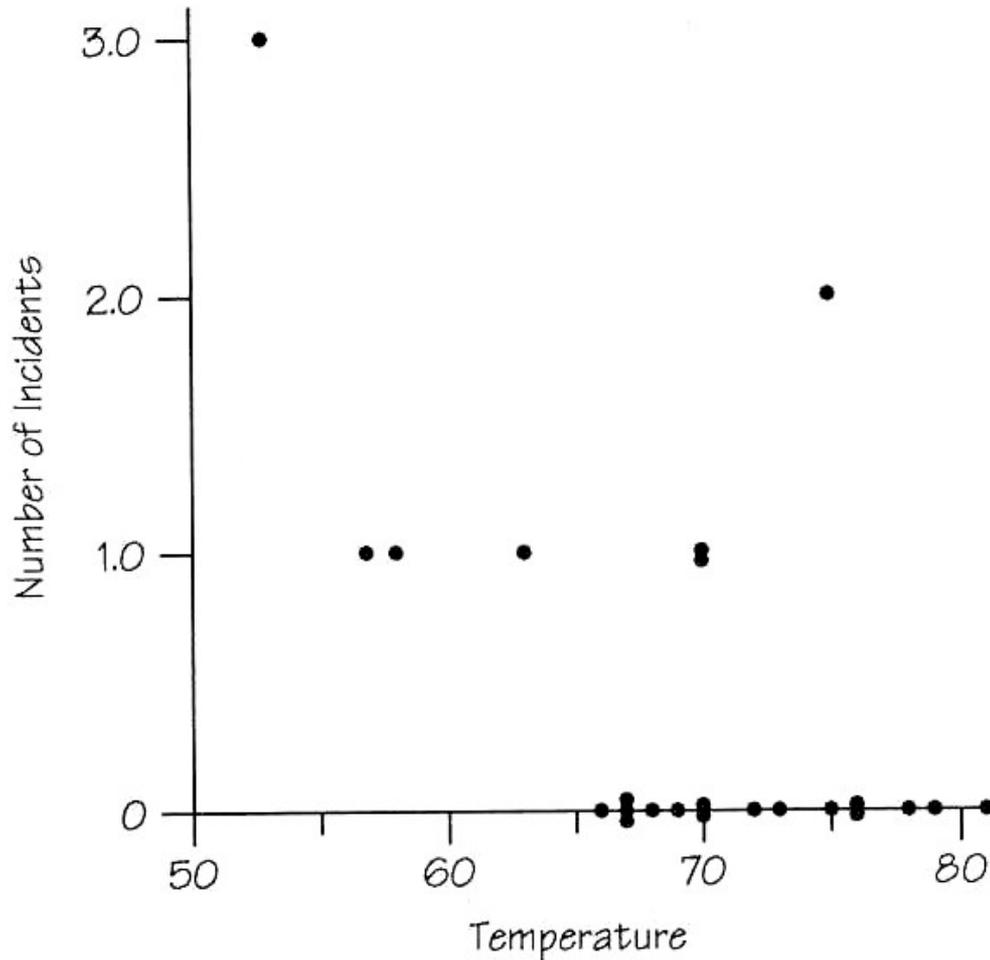


- Jon's examples show value of data analysis in the context of small, careful experiments
- For these processes to be successful, need to:
  - Use substantive knowledge of the problem, along with good ideas about possible models
  - Look at data in different ways, use EDA tools
  - Explore different variables
  - Iterate
- I'm a proponent for this approach to statistics, but there are also other key ideas in statistics that have proven useful
- My Discussion
  - Challenger example
  - Related (?) concepts
  - Network experiments

The Challenger data and scatter plot discussed in a conference call the night before launch.



The mistake was that the flights with zero incidents of damaged O-rings were left off the plot because it was felt that these flights did not contribute any information about the temperature effect. The scatter plot including *all* the data is shown below.



# Randomized Trials vis-à-vis Observational Studies and Modeling

- Randomization – great successes in agriculture, medicine, clinical trials
- Currently, economics of development aid ... “The basic idea behind the lab is to rely on randomized trials ... to study antipoverty programs” (*NY Times*, Feb. 20, 2008)
- Interesting editorial by David Freedman (*Chance*, Winter 2008)
- “Hiccups in data” – variables you didn’t know or think about, address via randomization?
- *Question: To what extent do, or do not, the concepts of randomized trials apply to the types of experiments Jon considers?*

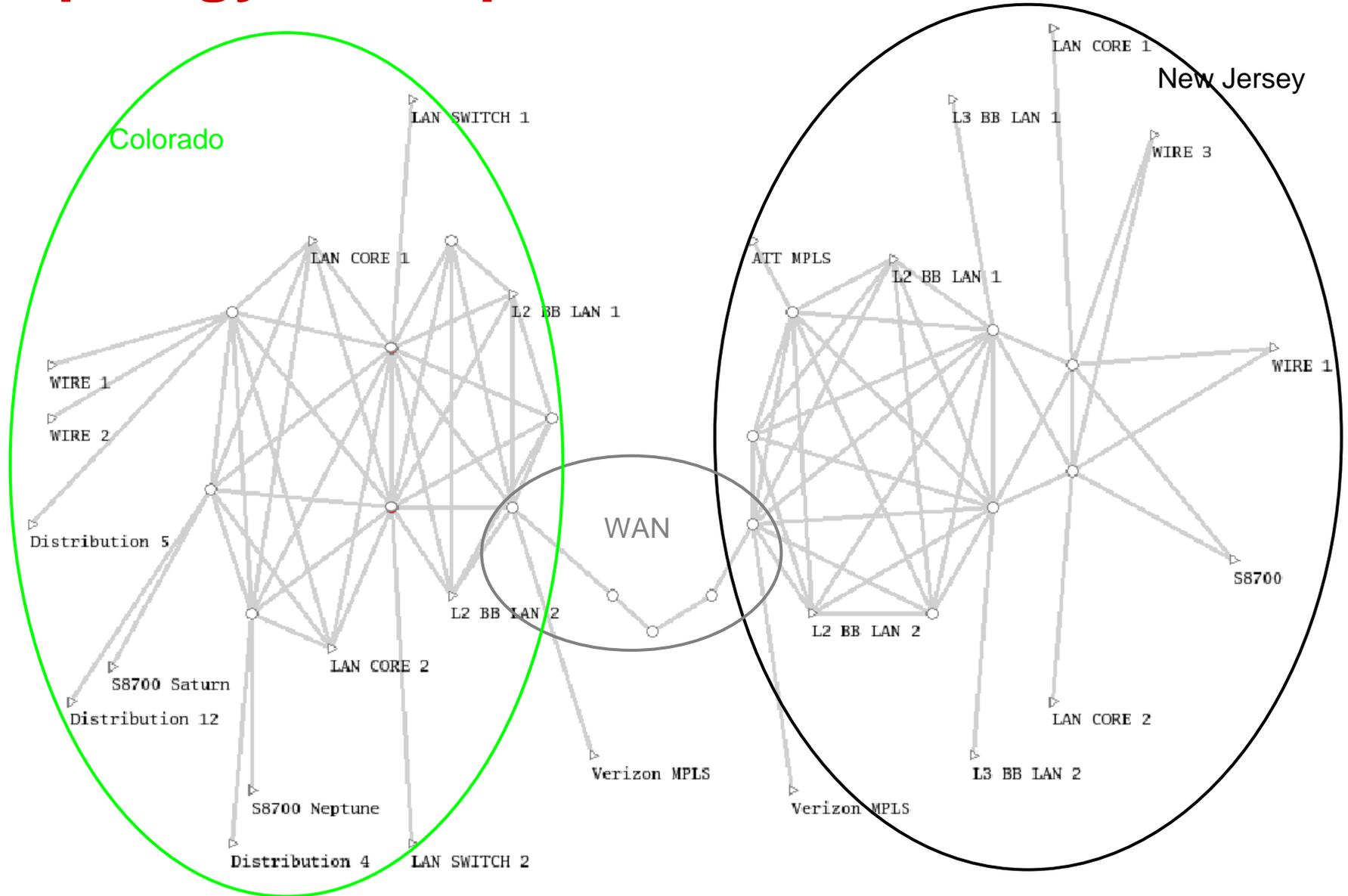
# Further Related Statistical Topics

- Blocking
  - Arrange experimental units into groups (blocks) so that the units in a block are similar to one another
  - Try for treatment comparisons within blocks
- Factorial experiments vis-à-vis one-factor-at-a-time experiments
  - Both types have roles
  - Are there situations where there might be interactions, leading to factorial experiments?
  - In order to reduce time to run experiment, do benefits from partial factorials apply?
  - Are purposes related to exploring a response surface, or more to establish/confirm/fit a theory?
- *Question: To what extent do, or do not, these concepts apply?*

# Experiments and Networks

- I will mention some issues and relationships to Jon's talk
- Problem Context: VoIP, video over corporate networks
- Goals:
  - Trouble shooting for intermittent problems
  - Provide ability to adapt to changing network conditions in real time, e.g. provide very high QoS and reliability for these applications
  - Evaluating network changes (today)
  - Evaluating possible changes to network equipment and structures (for tomorrow's uncertain applications and traffic)

# Topology of Corporate Network



# Testing and Experimentation Process

- End-to-end (E2E) tests across network
  - Use phones or special devices for testing
- Path across network for an E2E test does matter, it can change, and it needs to be discovered
- Analyst might or might not be able to select endpoint locations for the E2E tests
  - Sometimes can insert special tests
  - Sometimes use data from phone calls occurring naturally
- Implies that the analysis inherently involves tomography

# Mathematical Formulation

- Notation

$$Y_i = \begin{cases} 1 & \text{if test fails} \\ 0 & \text{if test succeeds} \end{cases}$$

$\mathbf{R}$  = routing matrix

$$R_{ij} = \begin{cases} 1 & \text{if the } j^{\text{th}} \text{ node (or edge) is involved in the } i^{\text{th}} \text{ test} \\ 0 & \text{otherwise} \end{cases}$$

for  $j = 1, \dots, K$  and  $K$  is total number of nodes (or edges)

$\pi_i$  = probability the  $i^{\text{th}}$  test fails

$p_j$  = probability that performance on this node fails

$\rho$  = probability test fails although none of the nodes directly "causes" failure

Then

$$Y_i \sim \text{Bernoulli}(\pi_i)$$

# Probability of Success

- End-to-end test success implies success on each traversed node and also for the background

$$(1 - \pi_i) = (1 - p) \times \prod_{\{j:R_{ij}=1\}} (1 - p_j)$$

- Log likelihood

$$C + \sum_{\{i:y_i=0\}} [\log(1 - p) + \sum_{\{j:R_{ij}=1\}} \log(1 - p_j)] + \sum_{\{i:y_i=1\}} \log(1 - [(1 - p) \times \prod_{\{j:R_{ij}=1\}} (1 - p_j)])$$

# Problems

- Likelihood a complicated non-linear expression
  - Could be intractable
  - Heuristics useful
- More fundamentally, truth can be on boundary of parameter space so standard asymptotic theory does not apply
- Hence, is likelihood analysis a good approach?
- *Real networks are large and raise complicated issues such as these in spades, so perhaps we should study the topic using Jon's ideas with careful, appropriately selected "small network experiments"?*

# Summary

- Congratulations to Jon for
  - His series of careful “small experiments”
  - For using data analysis creatively and successfully to gain insights
  - And for promoting the approach
- I’ve tried to raise questions on how, and whether or not, other statistical topics fit into experimentation in this domain
  - Randomized trials
  - Blocking variables
  - One-variable-at-a-time vis-à-vis factorial experimentation
  - Observational data and modeling vis-à-vis randomized controlled experiments
- Networks offer a fruitful area for pursuing these topics

# AVAYA *labs*

