Teaching DOX: Some Adventures and Lessons Learned

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About my class…

- IEE 572 Design of Engineering Experiments
- One-semester introductory graduate level course
- Offered both Fall & Spring semesters
- Audience is a mixed bag: industrial, electrical, chemical, civil, bio (and an occasional mechanical) engineers; material science, chemistry & physics, math and statistics students
- Sizable local industry participation

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- In addition to the on-campus class, there is also an on-line section
- Prerequisites are (theoretically) a first course in basic (or engineering) statistics
- Actual prerequisites consist of successfully answering three questions:
  - Are you familiar with the normal distribution?
  - Do you know how to compute the sample mean and standard deviation?
  - Have you been exposed to the *t*-test and the associated confidence interval?

- On-campus course enrollment varies between 75 and 100+ students per semester, on-line class sizes average about 25-30.
- One lecture section in a large hall; think freshman chemistry
- About 15% of a typical class consists of non-matriculating students from local industry
- Most on-line students are part-time students, pursuing MEng degrees
- About 50% of the students are required to take the course

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Some concepts that I try to get across…

All experiments are ***designed*** experiments; some of them are designed quite well, and some of them are designed really badly.

The badly designed ones often tell you very little.

We need to view designing and conducting an experiment as a **process**

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Seven steps to help ensure success (from Montgomery, D. C. (2005), *Design and Analysis of Experiments*, 6th edition, Wiley, New York)

1. Define the problem
2. Identify the response variable(s)
3. Determine the design factors, levels and ranges
4. Select the experimental design
5. Conduct the experiment
6. Analyze the data
7. Draw conclusions, recommendations

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- A large part of your success from a designed experiment results directly from how well you do the pre-experimental planning (steps 1-3 in the 7-step procedure).
- “If you had ten weeks to solve the problem, you should spend 8 weeks planning the experiment, one week conducting it, and one week analyzing the data”.

  - Professor C. R. Hicks, Purdue University
- See Coleman, D. E. and D. C. Montgomery (1993), "A Systematic Approach to Planning for a Designed Industrial Experiment," (with discussion), *Technometrics,* Vol. 35, No. 1, pp. 1-27.

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Course Schedule and Topics

(Based on two 75 minute Lectures per Week)

- Introduction and course overview (1 lecture)
- A simple comparative experiment (the two-sample *t*-test) (2-3 lectures)
- Strategy of experimentation (1 lecture)
- Single-factor CRDs; ANOVA basics (3 lectures)
- The blocking principle (2 lectures)
- Introduction to factorials (fixed effects model only) (2-3 lectures)
- Two-level factorials (3 lectures)
- Blocking and confounding in factorials (2 lectures)
- Two level fractional factorials (5-6 lectures)
- Response surface methods (overview) (2 lectures)
- Experiments with random factors (3 lectures)
- Nested and split-plot designs (2 lectures)

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Two term quizzes, final exam project

Step 5, conducting the experiment, presents ample opportunity for problems to occur

…something that I have not always fully appreciated

The “Aids to visually impaired pedestrians” experiment.

There were many factors, several responses, numerous subjects, runs spanning different time periods…*lots* of complications

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If something can go wrong when conducting an experiment, it probably will.

Pilot runs are often a good idea, particularly in complex experimental settings or "high-consequence" problems.

If you want an experiment run correctly, do it yourself.

"Flood-flow frequency on un-gauged watersheds"

A study to compare the performance of several methods in predicting the 100-year flood.

Many parties involved…USACE, USDA, USDT, FHA, NOAA, TVA, to name a few.

Lots of methods…ranging from simple to extremely complex.

Many different watershed types, located in different regions.

Training of experimental personnel a key issue.

The experimenters decided on a pilot study…sounds like a good idea, but…

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The pilot study ended up costing $1M (in 1980 $)!!

Never let one person design and conduct an experiment alone, particularly if that person is a subject-matter expert in the field of study.

Beware of complex, comprehensive experiments…the probability of successfully completing an experiment is inversely proportional to the number of runs.

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A personal success story (finally!): Wine-making.

Original vineyard property purchased in 1983. Objectives were to begin as a grape supplier to other winemakers, then develop a winemaking process.

Big problem: none of the partners were winemakers (how do you make a small fortune in wine…”).

However, some partners knew the power of designed experiments.

“Wine-making is a chemical process…I didn’t know how to make polymer, either, when I took my first job as a chemical engineer.”

There are many factors involved.

One experiment per year is all that is feasible.

Focus on Pinot Noir (Burgundy).

Factors considered for one year (1985):

Variable	Low Level (−)	High Level (+)
A = Pinot Noir clone	Pommard	Wadenswil
B = Oak type	Allier	Troncais
C = Age of barrel	Old	New
D = Yeast/skin contact	Champagne	Montrachet
E = Stems	None	All
F = Barrel toast	Light	Medium
G = Whole cluster	None	10%
H = Fermentation temperature	Low (75°F max)	High (92°F max)

The experimental design for 1985 is a fractional factorial:

Table 8-31 Design and Results for Wine Tasting Experiment

	Variable								Panel Rankings					Summary	
Run	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	HPN	JPN	CAL	DCM	RGB	$\bar{y}$	s
1	−	−	−	−	−	−	−	−	12	6	13	10	7	9.6	3.05
2	+	−	−	−	−	+	+	+	10	7	14	14	9	10.8	3.11
3	−	+	−	−	+	−	+	+	14	13	10	11	15	12.6	2.07
4	+	+	−	−	+	+	−	−	9	9	7	9	12	9.2	1.79
5	−	−	+	−	+	+	+	−	8	8	11	8	10	9.0	1.41
6	+	−	+	−	+	−	−	+	16	12	15	16	16	15.0	1.73
7	−	+	+	−	−	+	−	+	6	5	6	5	3	5.0	1.22
8	+	+	+	−	−	−	+	−	15	16	16	15	14	15.2	0.84
9	−	−	−	+	+	+	−	+	1	2	3	3	2	2.2	0.84
10	+	−	−	+	+	−	+	−	7	11	4	7	6	7.0	2.55
11	−	+	−	+	−	+	+	−	13	3	8	12	8	8.8	3.96
12	+	+	−	+	−	−	−	+	3	1	5	1	4	2.8	1.79
13	−	−	+	+	−	−	+	+	2	10	2	4	5	9.6	3.29
14	+	−	+	+	−	+	−	−	4	4	1	2	1	2.4	1.52
15	−	+	+	+	+	−	−	−	5	15	9	6	11	9.2	4.02
16	+	+	+	+	+	+	+	+	11	14	12	13	13	12.6	1.14

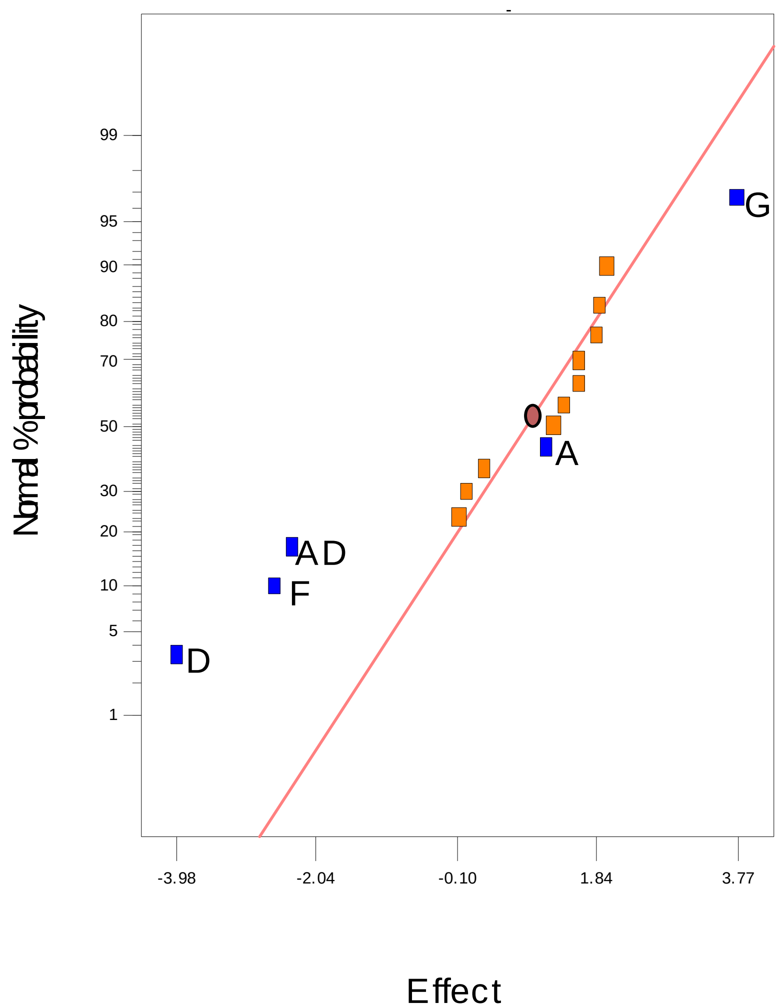
$\underbrace{\hspace{6em}}_{\text{Response is a forced rank}}$

Response is
a forced rank

Results for 1985:

A: PN Clone
B: Oak Type
C: Barrel Age
D: Yeast
E: Stems
F: Barrel Toast
G: Whole Cluster
H: Temp

[AD] = AD + CF + BH + EG



Some of the results are interesting and useful, such as

1. toasting the barrel a little more seems like a good idea, and
2. it doesn't seem to matter much where the oak comes from.

Some results are surprising such as no temperature effect!

There is an interaction: [AD] = AD + CF + BH + EG

Which effect(s) is real? CF and EG are more intuitive than AD

How would we normally resolve this?

1. Fold-over (be careful)?
2. Partial fold-over?
3. Other design augmentation strategies?

How did we do?

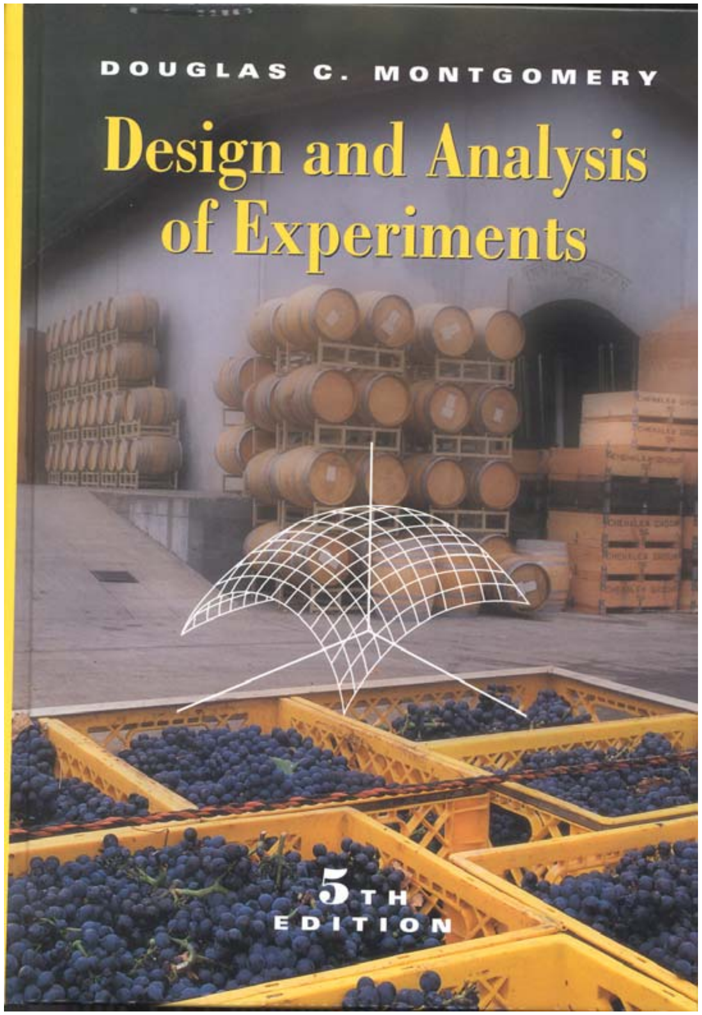
First commercial release, the1990 Pinot Noir, won a gold medal at the American Wine Competition

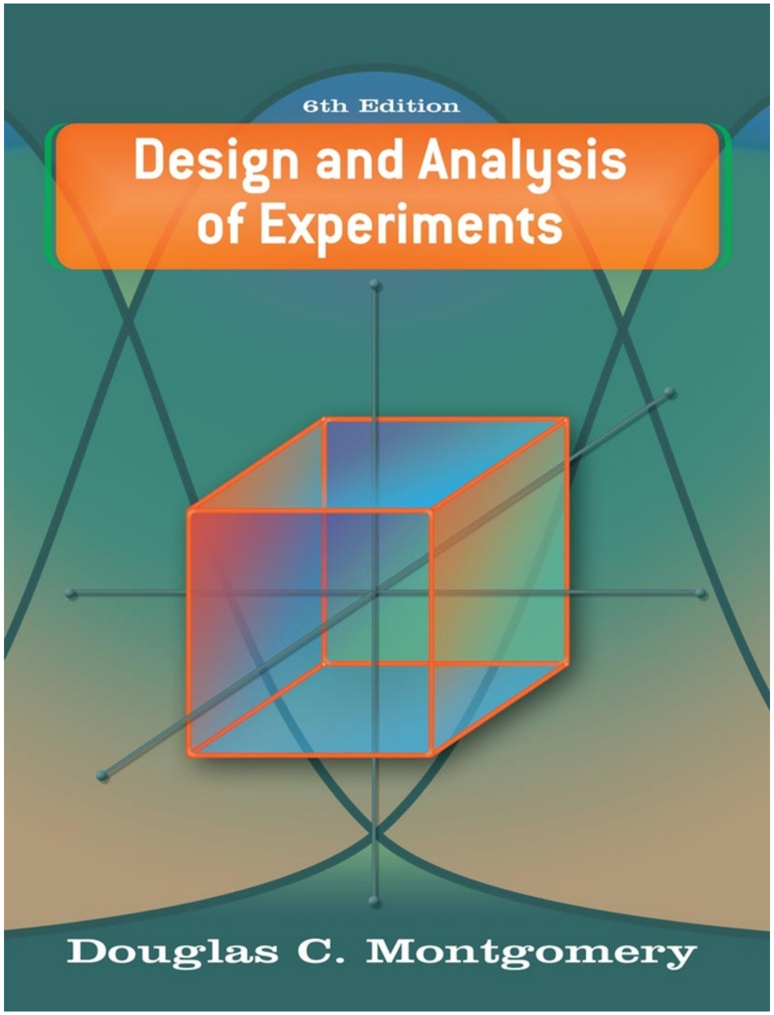
1991 release won a silver medal

1992 release won gold a medal, sixth best wine overall (of 2000 entries), best Oregon Pinot Noir

Consistently ranked by *The Wine Spectator* as among the best Pinot Noir available, 91-94 rating

Consistently highly rated in the International Pinot Noir Competition





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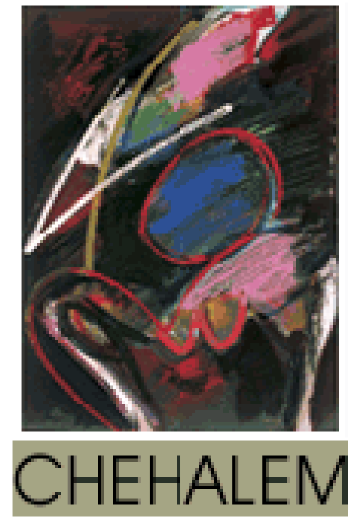

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Finally, my friend Stu Hunter has said that without good experimental design, we often end up doing PARC analysis. This is an acronym for

Planning **A**fter the **R**esearch is **C**omplete