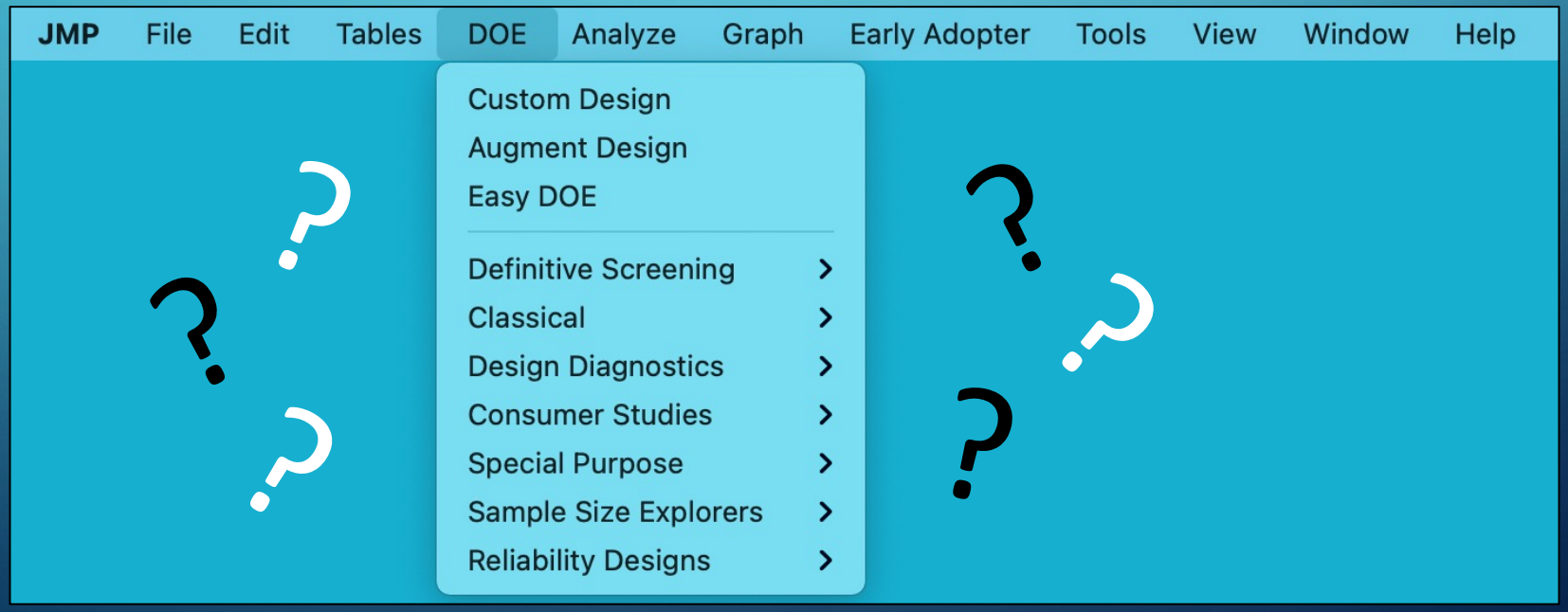
DESIGN OF EXPERIMENT'S CRUCIAL STEP 0: CHOOSING THE RIGHT DOE OPTION

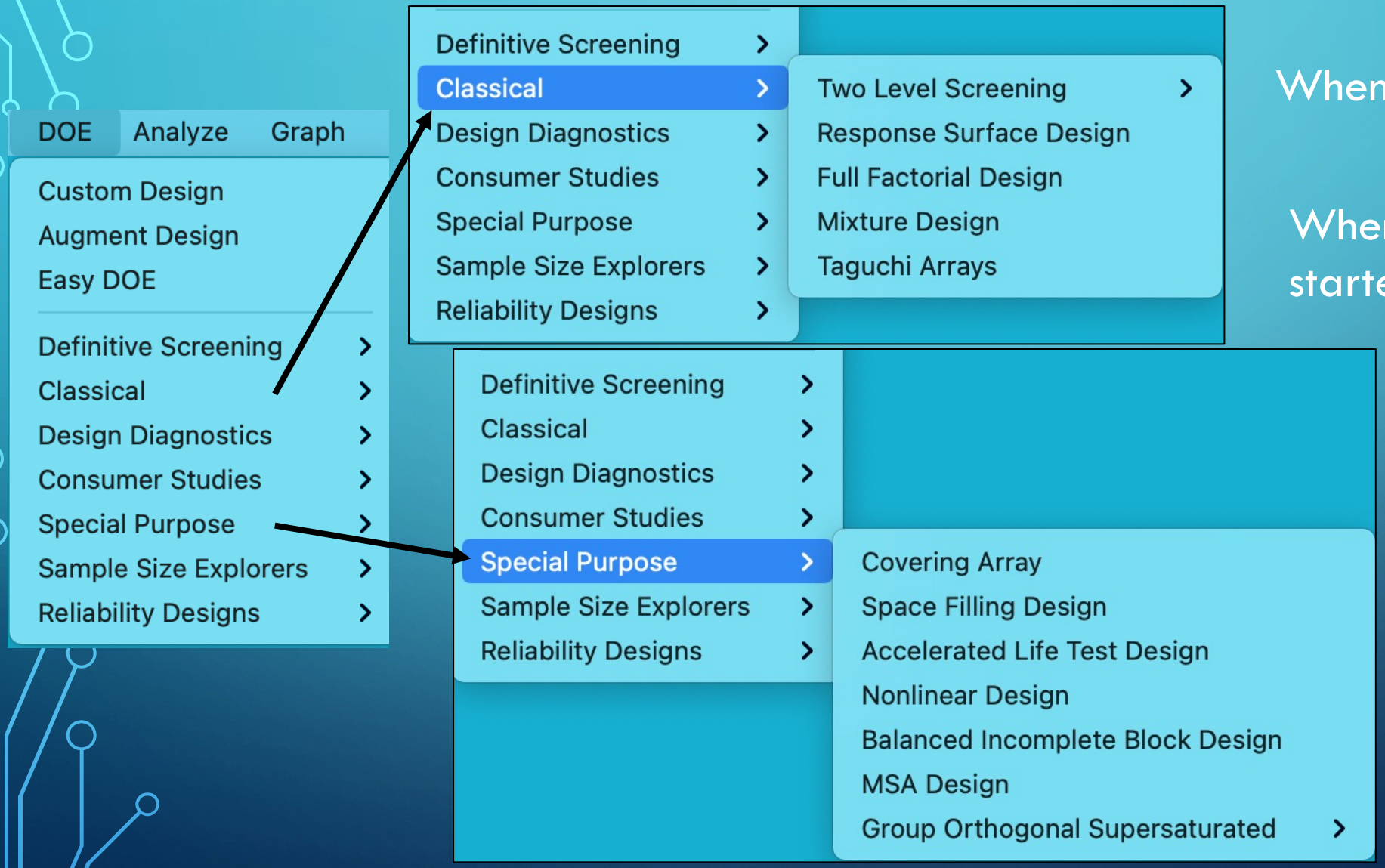
JMP Discovery Summit Americas 2023

Christine M. Anderson-Cook

candcook@gmail.com



CHOICES, CHOICES, CHOICES ….



When you are an expert ….

When you are getting started ….

OUTLINE

1. What are we trying to accomplish with our experiment?
   Understanding what the goal is of the experiment will help to match possible choices to our experiment

   NEEDS SUBJECT MATTER EXPERTISE!
2. What are the common DOE choices in JMP?
   Quick walk through of some of JMP's most popular design of experiment choices
3. Key Questions to consider before generating a design
   What do we already know about the factors, responses and their relationship?
   What are the constraints under which we need to operate?

   NEEDS SUBJECT MATTER EXPERTISE!

WHAT ARE WE TRYING TO DO? (EXPERIMENTAL OBJECTIVES)

1. Pilot Study – make sure that data quality and input space of interest is suitable
2. Exploration / Screening – identify important factors (eliminate those not important), see basic relationships
3. Modeling – capture relationship between inputs and response(s) in functional form
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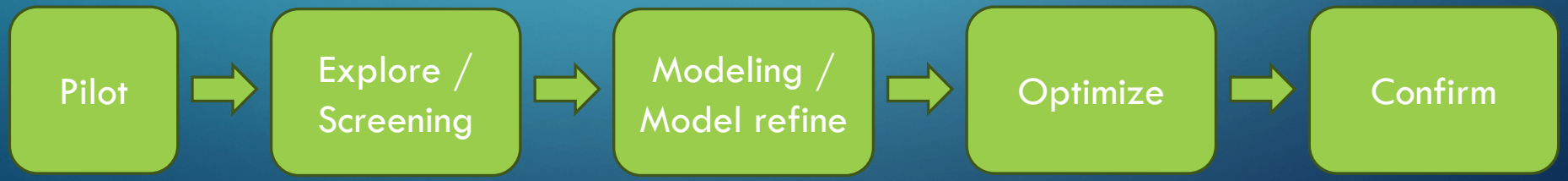

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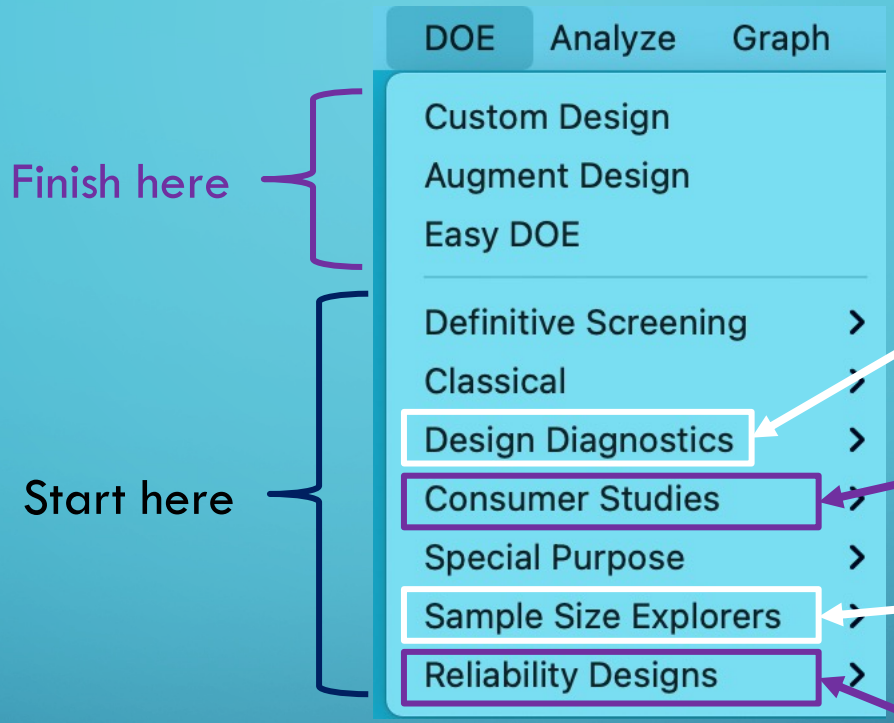


Not covered today

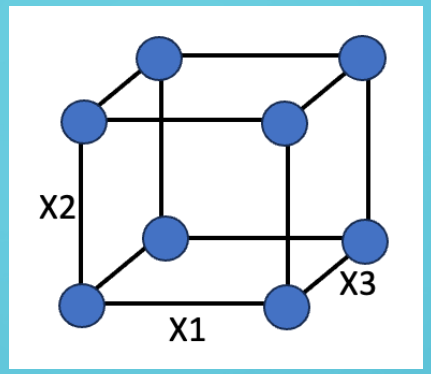
Understanding / Comparing performance of design

Designs for asking consumers their preferences

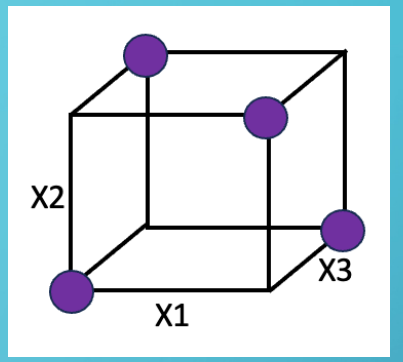
Tools for deciding size of experiment needed

Tools for design and analysis of reliability responses

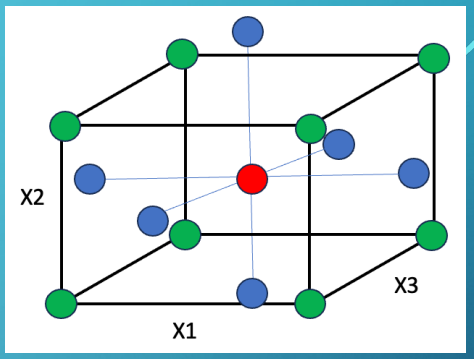
CLASSICAL DESIGNS – PART 1



Full Factorial



Two-Level Screening

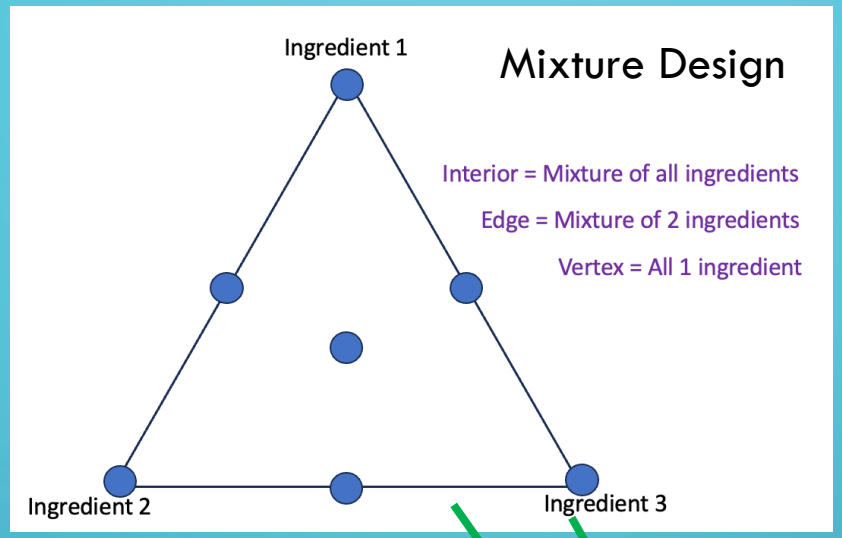


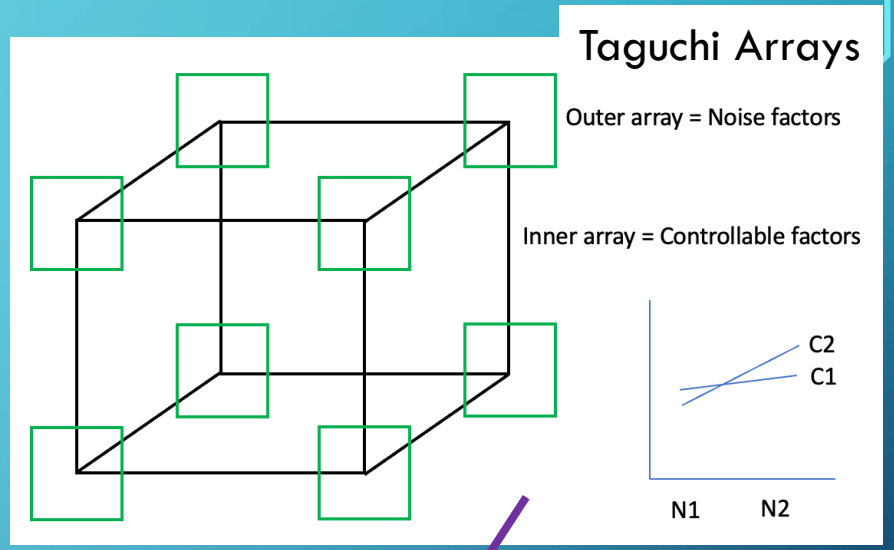
Response Surface

- Key characteristics:
  - Designed for standard situations with pre-specified regions and # of runs
  - Good overall performance
- Purpose:
  - Screening & Modeling

1. Pilot Study
2. Exploration / Screening
3. Modeling
4. Model Refinement
5. Optimize
6. Confirm

CLASSICAL DESIGNS – PART 2





- Key characteristics:
  - Special situations:
    - Mix = when proportions of ingredients matters
    - Tag = making process robust to things we can't control in production
- Purpose:
  - Mix = Screening & Modeling
  - Tag = Optimizing robustness

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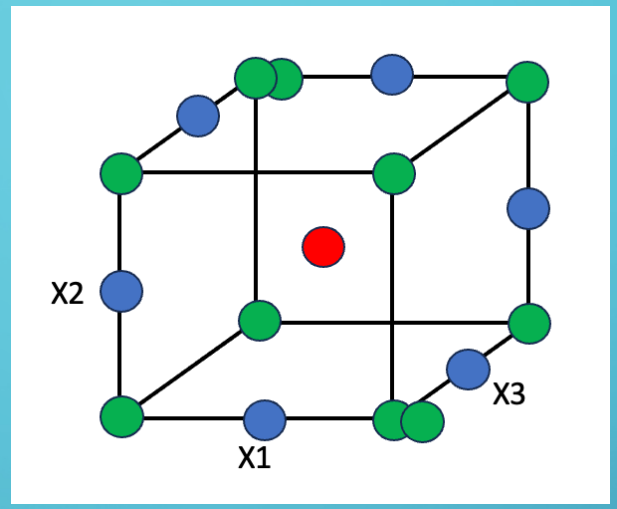
DEFINITIVE SCREENING DESIGN

- Key characteristics:
  - Allows screening for important factors, but also exploration for curvature
  - Specialized analysis
- Purpose:
  - Screening & Modeling



1. Pilot Study
2. Exploration / Screening
3. Modeling
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5. Optimize
6. Confirm

Σ	X1	X2	X3
1	0	1	1
2	0	-1	-1
3	1	0	1
4	-1	0	-1
5	1	-1	0
6	-1	1	0
7	1	-1	-1
8	-1	1	1
9	1	1	-1
10	-1	-1	1
11	1	-1	1
12	-1	1	-1
13	1	1	-1
14	-1	-1	1
15	1	1	1
16	-1	-1	-1
17	0	0	0

SPECIAL PURPOSE – COVERING ARRAY

Runs →

	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	0	0	0	0	0	0
2	1	1	1	1	1	1	1	1	1	1
3	1	1	1	0	1	0	0	0	0	1
4	1	0	1	1	0	1	0	1	0	0
5	1	0	0	0	1	1	1	0	0	0
6	0	1	1	0	0	1	0	0	1	0
7	0	0	1	0	1	0	1	1	1	0
8	1	1	0	1	0	0	1	0	1	0
9	0	0	0	1	1	1	0	0	1	1
10	0	0	1	1	0	0	1	0	0	1
11	0	1	0	1	1	0	0	1	0	0
12	1	0	0	0	0	0	0	1	1	1
13	0	1	0	0	0	1	1	1	0	1

← Factors

Example: All combinations of levels for any 3 factors appear at least once

- Key characteristics:
  - Want to test if combinations of factors cause problems
  - Ideal for testing of software across very large number of combinations
- Purpose:
  - Exploration

1. Pilot Study
2. **Exploration / Screening**
3. Modeling
4. Model Refinement
5. Optimize
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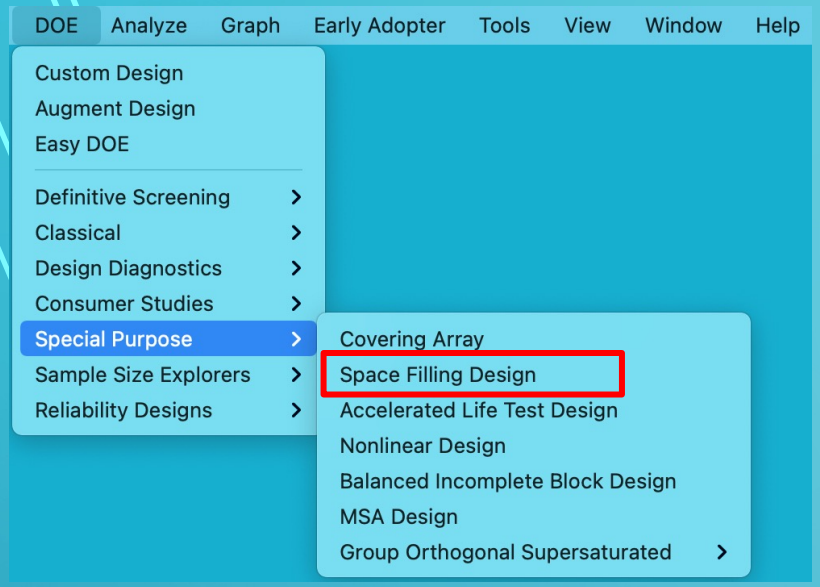
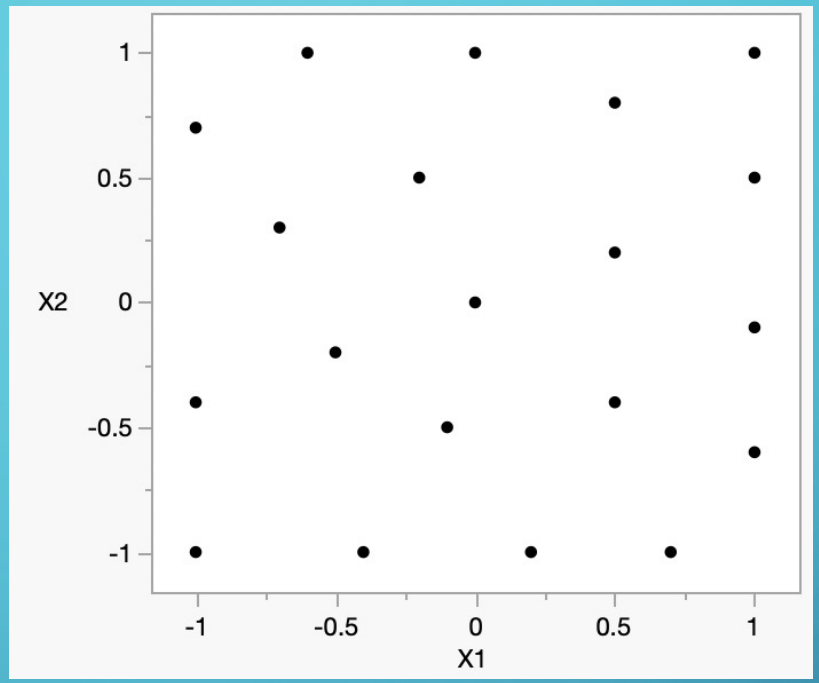
SPECIAL PURPOSE – SPACE FILLING





- Sphere Packing
- Latin Hypercube
- Uniform
- Minimum Potential
- Maximum Entropy
- Gaussian Process IMSE Optimal
- Fast Flexible Filling

- Key characteristics:
  - Good option if little is known about underlying relationship
  - Common in computer experiments
- Purpose:
  - Exploration & Modeling

1. Pilot Study
2. Exploration / Screening
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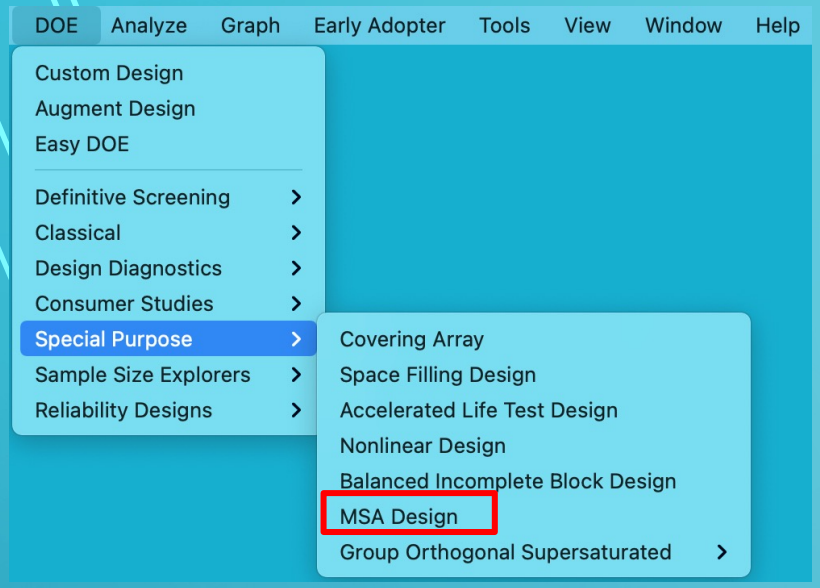
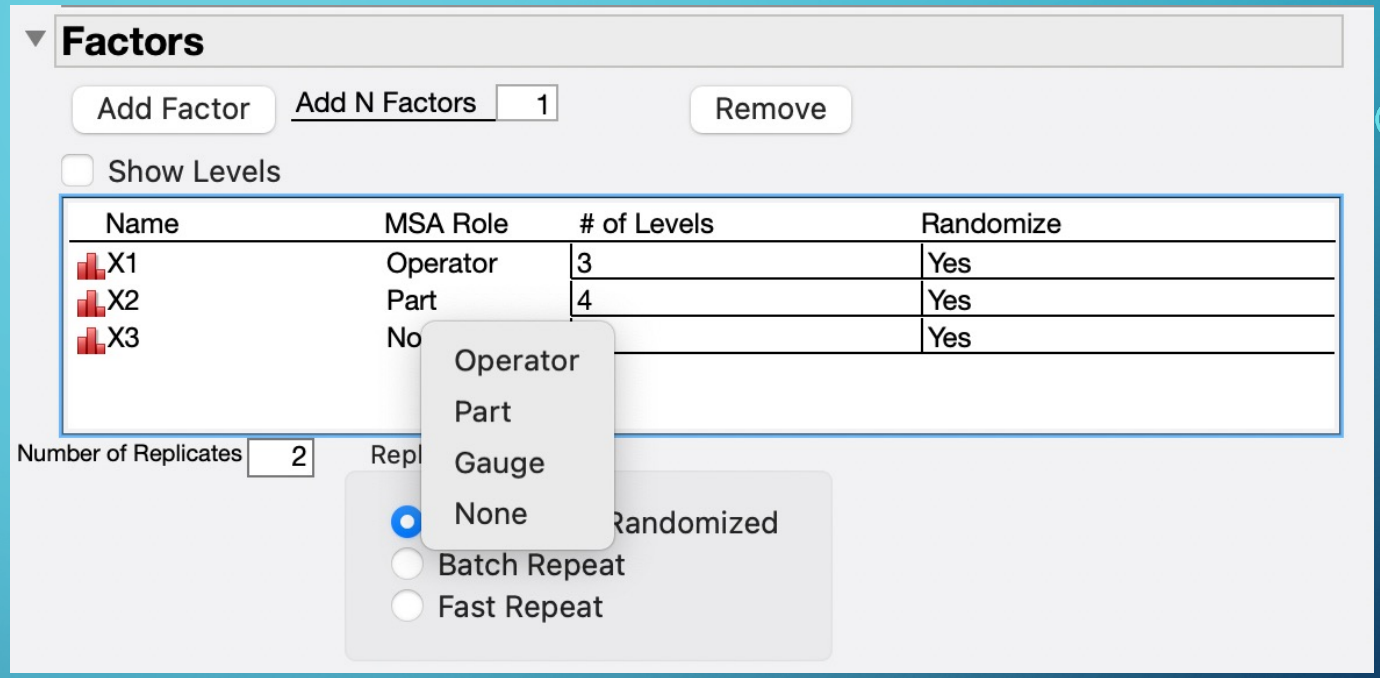
SPECIAL PURPOSE – MSA DESIGN (MEASUREMENT SYSTEM ANALYSIS)





- Key characteristics:
  - Design to characterize sources of variability
  - Assess precision of measurement system
- Purpose:
  - Pilot study – data adequacy

1. Pilot Study
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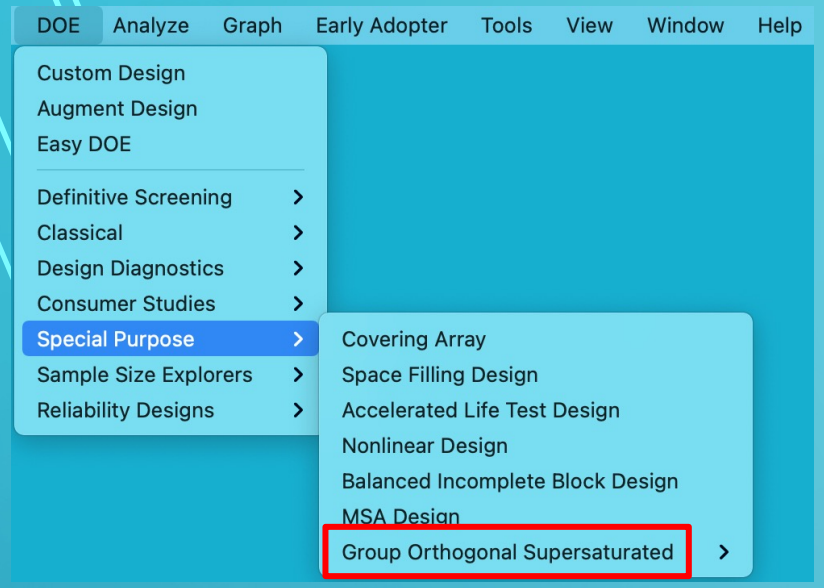
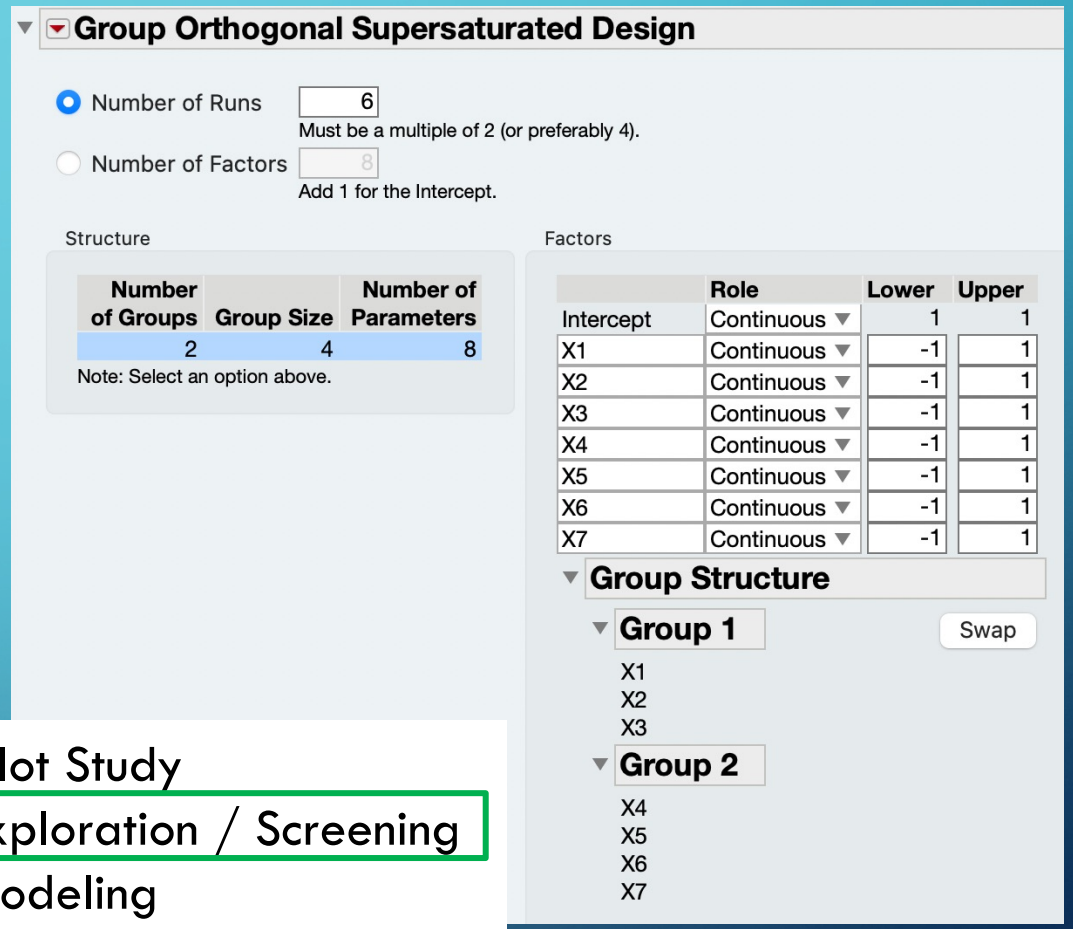
SPECIAL PURPOSE – GROUP ORTHOGONAL SUPERSATURATED





- Key characteristics:
  - When # factors > # runs
  - Complementary analysis to identify important factors
  - Important to not have too many active factors
- Purpose:
  - Exploration / Screening

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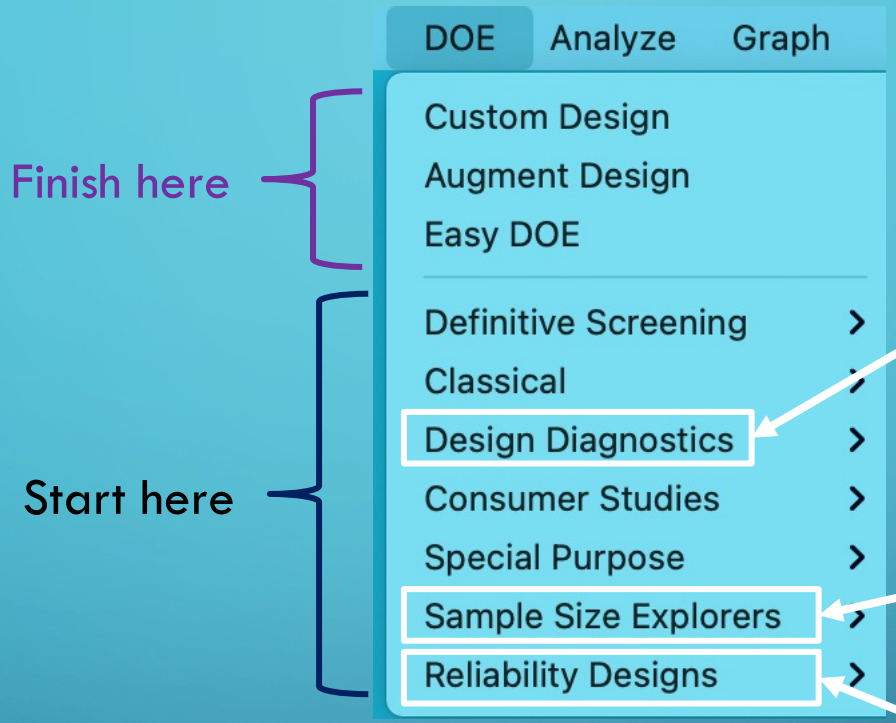
CHOICES



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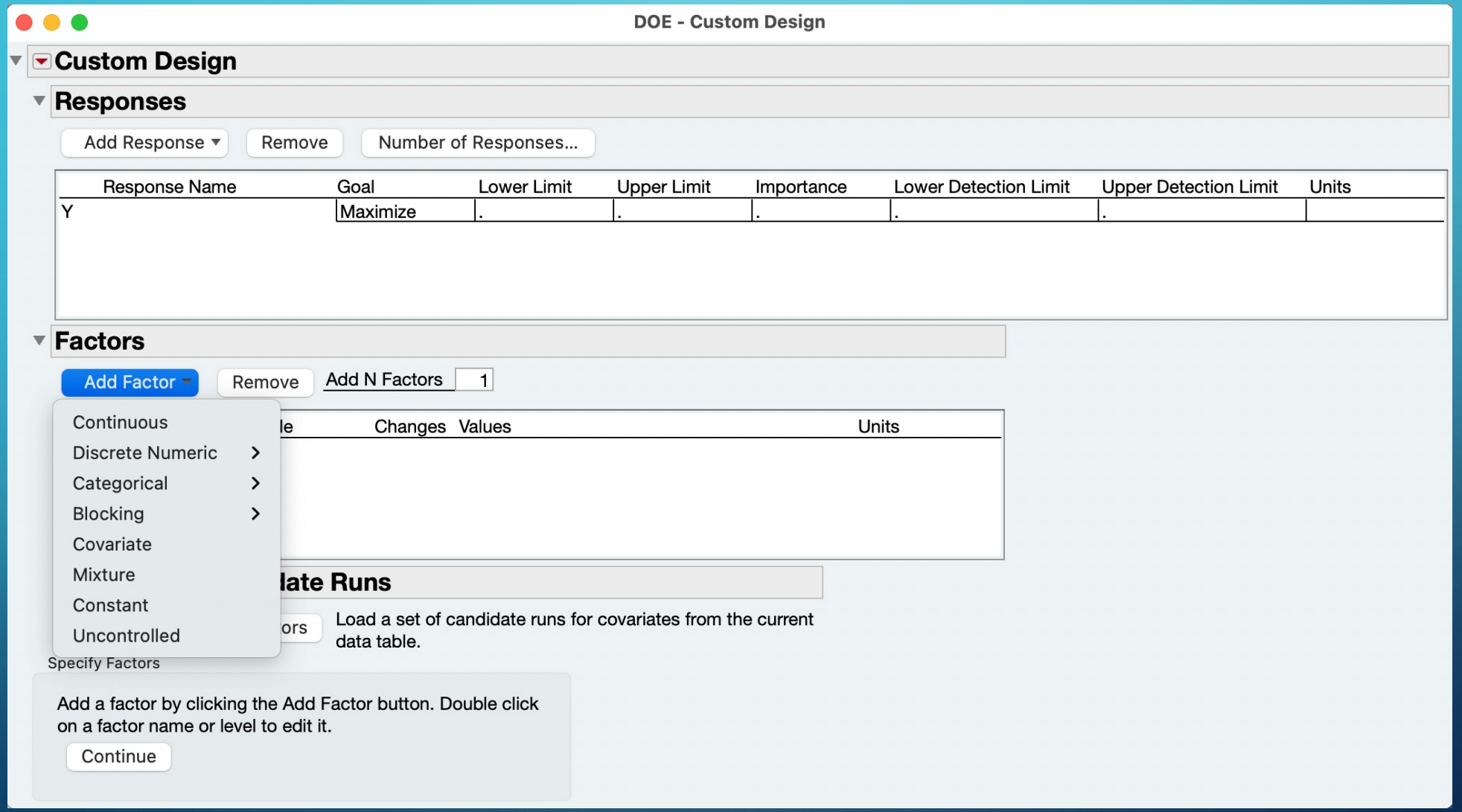
Tools for deciding size of experiment needed

Tools for design and analysis of reliability responses

CUSTOM DESIGN TO THE RESCUE!!



THINK SEQUENTIALLY – AUGMENT!

	X1	X2	X3	Y
1	1	-1	-1	7
2	1	-1	1	15
3	0	0	-1	2
4	-1	1	1	5
5	-1	-1	1	9
6	0	0	1	10
7	1	0	0	9
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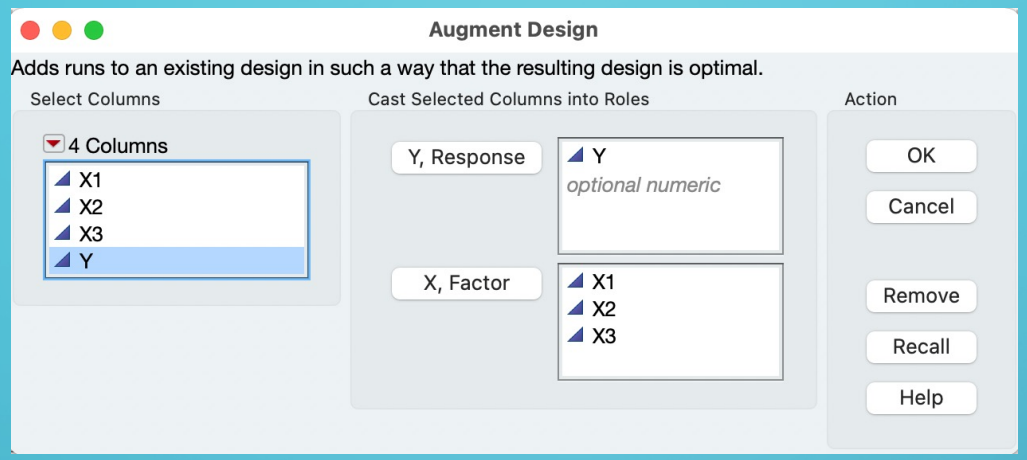
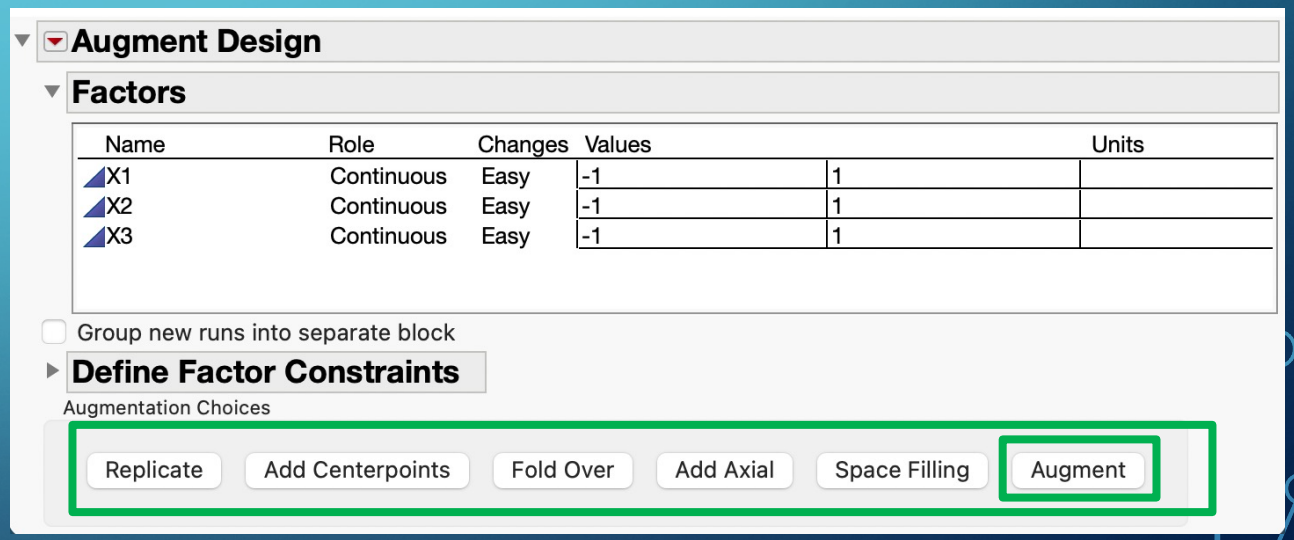
9	-1	1	-1	-3
10	0	-1	0	8
11	1	1	1	11
12	0	1	0	4
13	1	1	-1	3
14	0	0	0	6
15	-1	0	0	3





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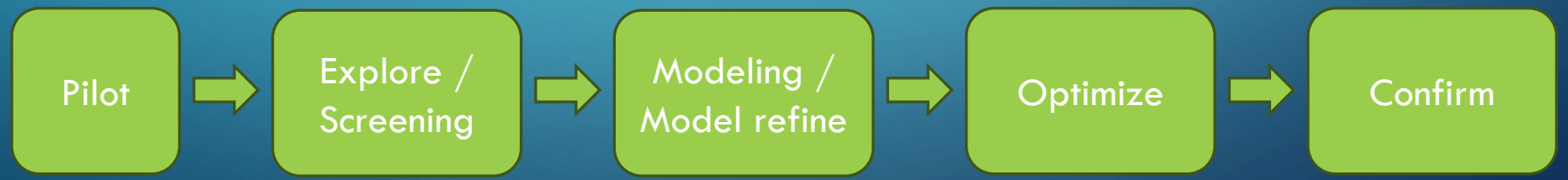
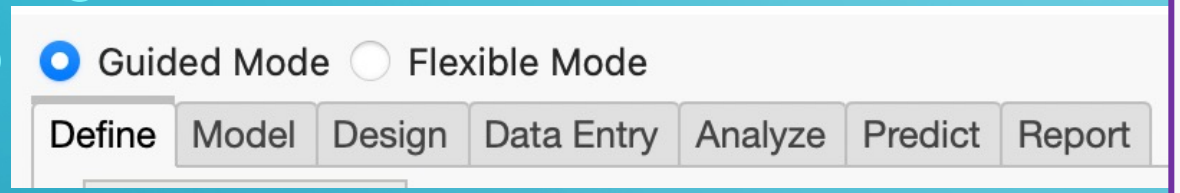
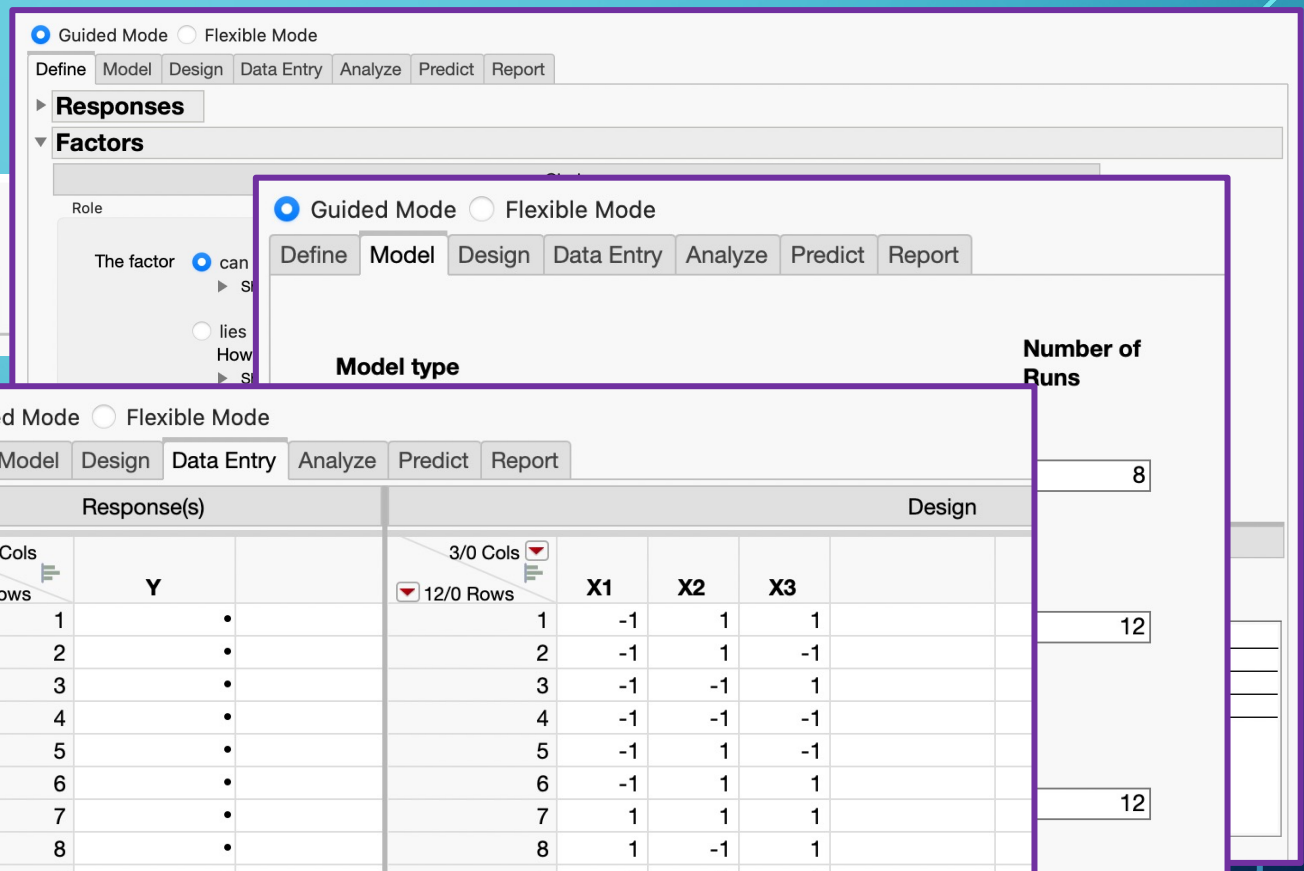


EASY DOE – HELP WITH DESIGN AND ANALYSIS





- Key characteristics:
  - Assumes you want to do screening or modeling
  - Will guide you through all steps of building, running and analyzing the experiment
- Purpose:
  - Exploration & Modeling

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WHAT DO WE ALREADY KNOW?

Factors:

- Which ones?
  - Too many → experiment will need to be large to understand them all
  - Too few → possibility of missing something important
- What type are they?

Continuous
Discrete Numeric
Categorical
Blocking
Covariate
Mixture
Constant
Uncontrolled

- What ranges / values for each?
  - Too big → difficult to understand what is happening, miss a subtle feature
  - Too small → miss target location, effect of factors look very small
  - Wrong location → miss target location

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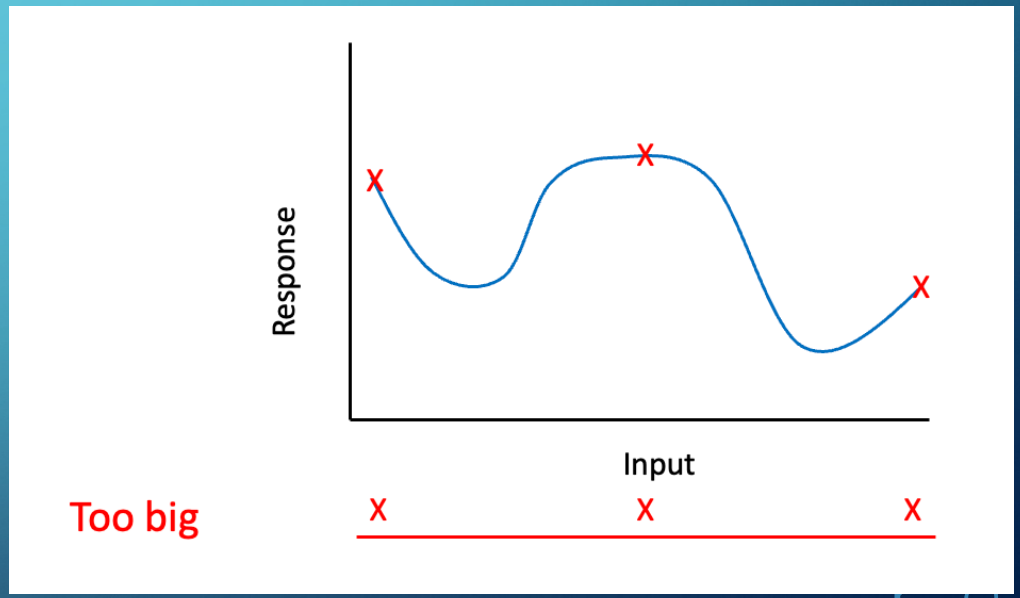

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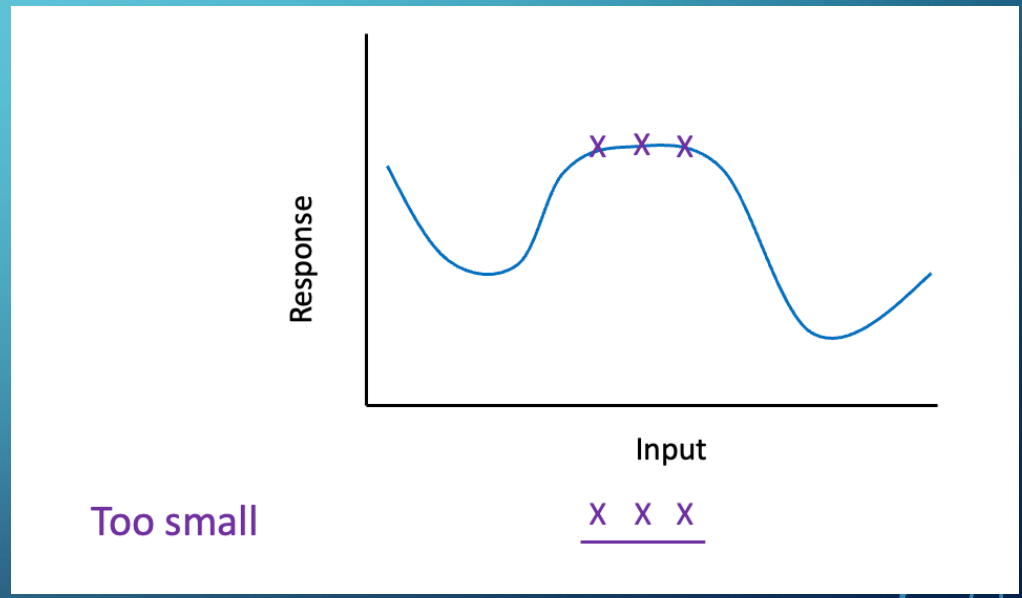

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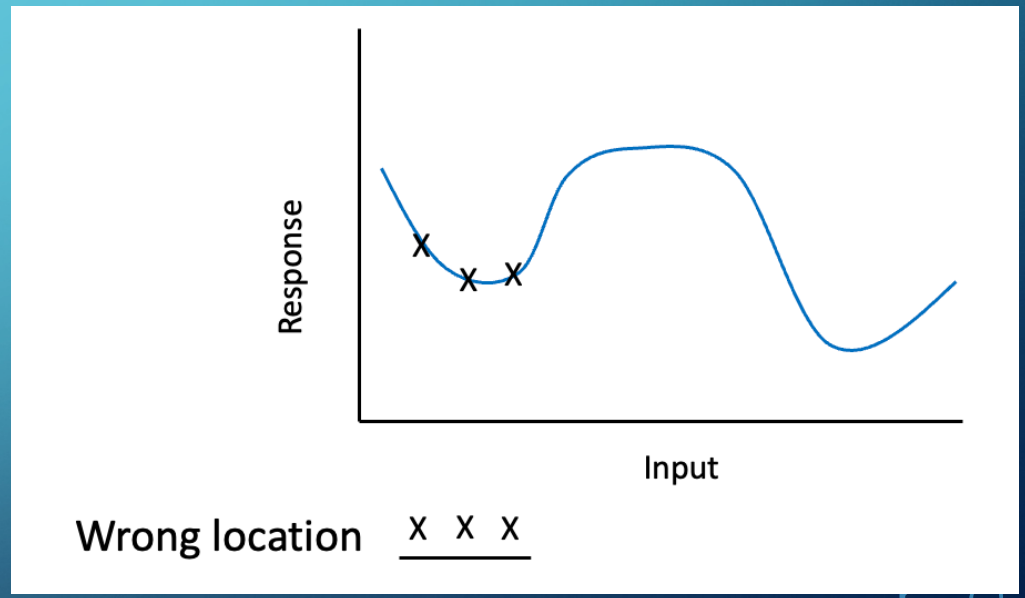


WHAT DO WE ALREADY KNOW?

Relationship between inputs and responses:

- Which responses are we interested in? [COMMON MISTAKE: forgetting an important response]
- What do we know about the relationships?
  - Continuous
  - Smooth
  - Complexity
    - First-order (main effects) – common for screening
    - Interactions
    - Curvature

  [COMMON MISTAKES: - assuming you know too much
  - not designing for most complicated relationship]

- First key decision: model-based (confident in smooth continuous, not too big a region)
  or space-filling (not sure what to expect, large region, protects against surprises)

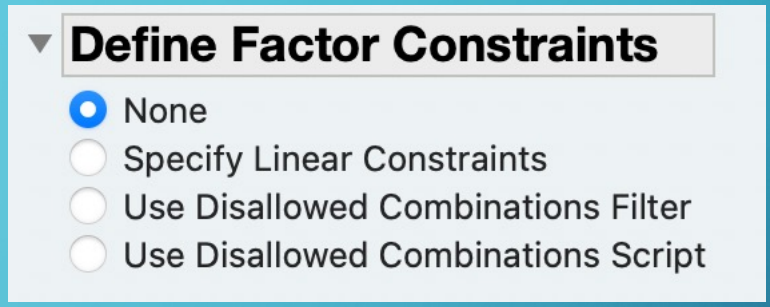
Anderson-Cook and Lu, 2021

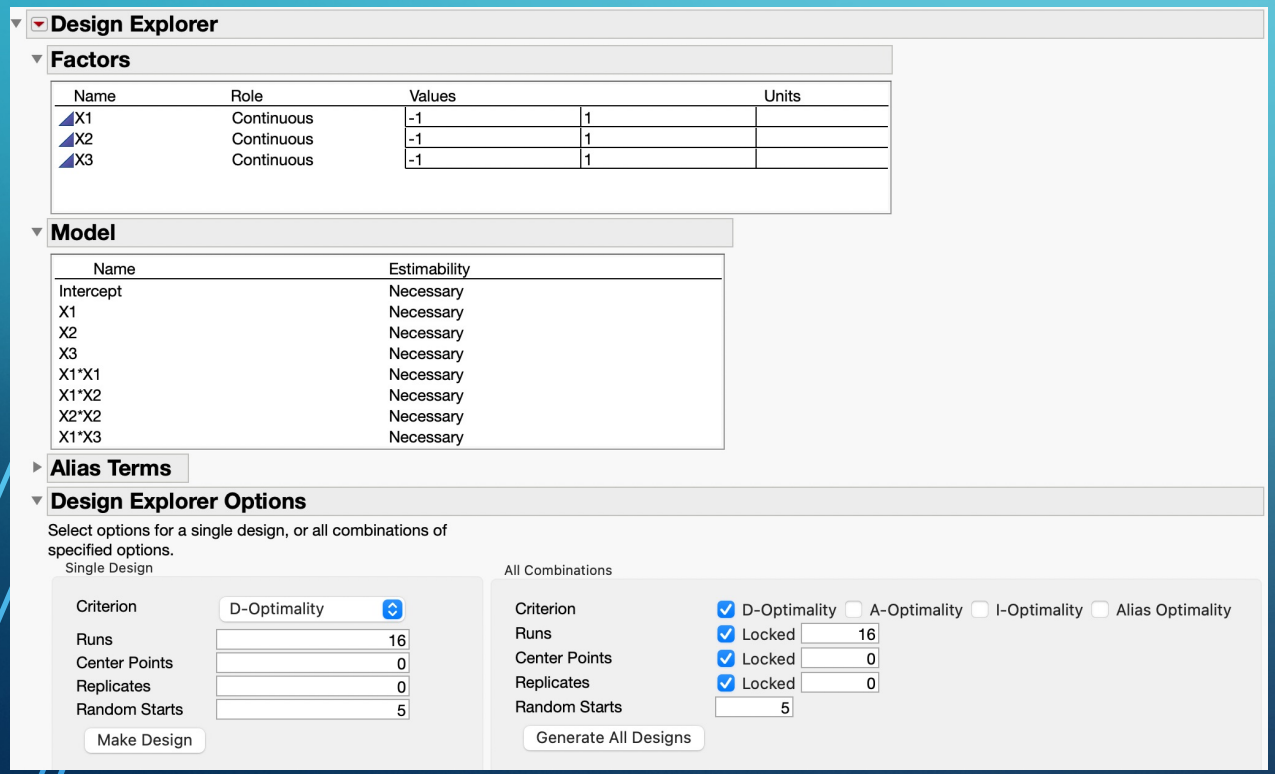
CONSTRAINTS?

- Input regions / combinations where responses not possible?
  not of interest?

- Budget?
  - Time
  - Cost

} Better to think in terms of ranges for # of runs, and then compare several designs





JMP White Paper: Benefits of considering several different design sizes
Anderson-Cook, 2022

HELPFUL RESOURCES

Types of Designed Experiments:
https://www.jmp.com/en_in/statistics-knowledge-portal/what-is-design-of-experiments/types-of-design-of-experiments.html

Model-Based versus Space-Filling:
Anderson-Cook, C.M. Lu, L. (2021) “The First Fork in the Road” Quality Progress 54(11) 48-51.

Considering and comparing several design sizes and types:
JMP White Paper: Anderson-Cook, 2022
https://www.jmp.com/en_us/whitepapers/jmp/choosing-the-right-design.html

The Why and How of Asking Good Questions:
JMP White Paper: Anderson-Cook, 2023
www.jmp.com/asking-good-questions