Quantitative and Qualitative Methods for Human-Subject Experiments in Virtual and Augmented Reality

VR 2012 Tutorial

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Motivation and Goals

- **Studying experimental design and analysis at Mississippi State University:**
    - PSY 3103 Introduction to Psychological Statistics
    - PSY 3314 Experimental Psychology
    - PSY 6103 Psychometrics
    - PSY 8214 Quantitative Methods In Psychology II
    - PSY 8803 Advanced Quantitative Methods
    - IE 6613 Engineering Statistics I
    - IE 6623 Engineering Statistics II
    - ST 8114 Statistical Methods
    - ST 8214 Design & Analysis Of Experiments
    - ST 8853 Advanced Design of Experiments I
    - ST 8863 Advanced Design of Experiments II

- **7 undergrad hours; 30 grad hours; 3 departments!**

- **Course attendee backgrounds?**

Motivation and Goals

- **What can we accomplish in one day?**

- **Study subset of basic techniques**
  - Presenters have found these to be the most applicable to VR, AR systems

- **Focus on intuition behind basic techniques**

- **Become familiar with basic concepts and terms**
  - Facilitate working with collaborators from psychology, industrial engineering, statistics, etc.

Why Human Subject (HS) Experiments?

- **Graphics hardware / software more mature**
- **Sophisticated interactive techniques possible**

- **Focus of field:**
  - Implementing technology $\rightarrow$ using technology
  - Trend at IEEE Visualization, SIGGRAPH
  - Called for in *NIH-NSF Visualization Research Challenges Report* [Johnson et al 06]

- **Increasingly running HS experiments:**
  - How do humans perceive, manipulate, cognate with CG-mediated information?
  - Measure utility of VR / AR for applications

Outline

- *Experimental Validity*

- Experimental Design

- Describing Data

  – Graphing Data

  – Descriptive Statistics

- Inferential Statistics

  – Hypothesis Testing

  – Analysis of Variance

  – Power

- Graphical Data Analysis

The Empirical Method

- **The *Empirical Method*:**
  - Develop a hypothesis, perhaps based on a theory
  - Make the hypothesis testable
  - Develop an empirical experiment
  - Collect and analyze data
  - Accept or refute the hypothesis
  - Relate the results back to the theory
  - If worthy, communicate the results to scientific community

- **Statistics:**
  - Foundation for empirical work; necessary but not sufficient
  - Often not useful for managing problems of gathering, interpreting, and communicating empirical information.

Designing Valid Empirical Experiments

- **Experimental Validity**
  - Does experiment really measure what we want it to measure?
  - Do our results really mean what we think (and hope) they mean?
  - Are our results reliable?
    - If we run the experiment again, will we get the same results?
    - Will others get the same results?

- **Validity is a large topic in empirical inquiry**

Experimental Variables

- **Independent Variables**
  - What the experiment is studying
  - Occur at different **levels**
    - Example: stereopsis, at the levels of stereo, mono
  - Systematically varied by experiment

- **Dependent Variables**
  - What the experiment measures
  - Assume dependent variables will be effected by independent variables
  - Must be measurable quantities
    - Time, task completion counts, error counts, survey answers, scores, etc.
    - Example: VR navigation performance, in total time

Experimental Variables

- **Independent variables can vary in two ways**
  - **Between-subjects: each subject sees a different level of the variable**
    - **Example: ½ of subjects see stereo, ½ see mono**
  - **Within-subjects: each subject sees all levels of the variable**
    - **Example: each subject sees both stereo and mono**

- **Confounding factors (or confounding variables)**
  - **Factors that are not being studied, but will still affect experiment**
    - **Example: stereo condition less bright than mono condition**
  - **Important to predict and control confounding factors, or experimental validity will suffer**

Experimental Design

- **Experimental Validity**

- *Experimental Design*

- **Describing Data**

  - **Graphing Data**

  - **Descriptive Statistics**

- **Inferential Statistics**

  - **Hypothesis Testing**

  - **Analysis of Variance**

  - **Power**

- **Graphical Data Analysis**

Experimental Designs

- **2 x 1** is simplest possible design, with one independent variable at two levels:

Variable
level 1
level 2

Stereopsis
stereo
mono

- **Important confounding factors for within subject variables:**
  - Learning effects
  - Fatigue effects
- **Control these by counterbalancing the design**
  - Ensure no systematic variation between levels and the order they are presented to subjects

Subjects	1st condition	2nd condition
1, 3, 5, 7	stereo	mono
2, 4, 6, 8	mono	stereo

Factorial Designs

- *n* x 1 designs generalize the number of levels:

VE terrain type
flat
hilly
mountainous

- **Factorial designs** generalize number of independent variables and the number of levels of each variable

- **Examples:** *n* x *m* design, *n* x *m* x *p* design, etc.

- **Must watch for factorial explosion of design size!**

3 x 2 design:

VE terrain type	Stereopsis	
	stereo	mono
flat		
hilly		
mountainous		

Cells and Repetitions

- **Cell**: each combination of levels
- **Repetitions**: typically, the combination of levels at each cell is repeated a number of times

VE terrain type	Stereopsis	
	stereo	mono
flat		
hilly		
mountainous		

cell

- **Example of how this design might be described:**
  - "A 3 (VE terrain type) by 2 (stereopsis) within-subjects design, with 4 repetitions of each cell."
  - This means each subject would see 3 x 2 x 4 = 24 total conditions
  - The presentation order would be counterbalanced

Counterbalancing

- **Addresses time-based confounding factors:**
  - **Within-subjects variables: control learning and fatigue effects**
  - **Between-subjects variables: control calibration drift, weather, other factors that vary with time**

- **There are two counterbalancing methods:**
  - **Random permutations**
  - **Systematic variation**
    - **Latin squares are a very useful and popular technique**

$$\begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix}$$

2 x 2

$$\begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 3 & 2 \\ 2 & 1 & 3 \\ 3 & 2 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 & 3 & 4 \\ 2 & 4 & 1 & 3 \\ 3 & 1 & 4 & 2 \\ 4 & 3 & 2 & 1 \end{bmatrix}$$

4 x 4

- **Latin square properties:**
  - **Every level appears in every position the same number of times**
  - **Every level is followed by every other level**
  - **Every level is preceded by every other level**

6 x 3 (there is no 3 x 3 that has all 3 properties)

Counterbalancing Example

- "A 3 (VE terrain type) by 2 (stereopsis) within-subjects design, with 4 repetitions of each cell."

- Form Cartesian product of Latin squares
{6 x 3} (VE Terrain Type) ⊗ {2 x 2} (Stereopsis)

- Perfectly counterbalances groups of 12 subjects

$$\begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 1 \\ 3 & 1 & 2 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 3 & 2 \\ 2 & 1 & 3 \\ 3 & 2 & 1 \end{bmatrix}$$

$$\begin{bmatrix} A & B \\ B & A \end{bmatrix}$$

Subject	Presentation Order
1	1A, 1B, 2A, 2B, 3A, 3B
2	1B, 1A, 2B, 2A, 3B, 3A
3	2A, 2B, 3A, 3B, 1A, 1B
4	2B, 2A, 3B, 3A, 1B, 1A
5	3A, 3B, 1A, 1B, 2A, 2B
6	3B, 3A, 1B, 1A, 2B, 2A
7	1A, 1B, 3A, 3B, 2A, 2B
8	1B, 1A, 3B, 3A, 2B, 2A
9	2A, 2B, 1A, 1B, 3A, 3B
10	2B, 2A, 1B, 1A, 3B, 3A
11	3A, 3B, 2A, 2B, 1A, 1B
12	3B, 3A, 2B, 2A, 1B, 1A

Experimental Design Example #1

trial number	1 216	217 432

sv[1]

ground plane	on		off	
stereo	on	off	on	off

rp[2]

drawing style	wire		fill		wire+fill	
alpha	const	decr	const	decr	const	decr
intensity	const	decr	const	decr	const	decr	const	decr	const	decr	const	decr

rp[2]

target position	close		middle		far	
repetition	1	2	3	1	2	3	1	2	3

[1] sv = systemically varied, [2] rp = randomly permuted

- **All variables within-subject**

From [Living Swan et al. 03]

Experimental Design Example #2

Between Subject	Stereo Viewing		on				off			
	Control Movement		rate		position		rate		position	
	Frame of Reference		ego	exo	ego	exo	ego	exo	ego	exo
Within Subject	Computer Platform	cave	subjects 1 – 4	subjects 5 – 8	subjects 9 – 12	subjects 13 – 16	subjects 17 – 20	subjects 21 – 24	subjects 25 – 28	subjects 29 – 32
		wall								
		workbench								
		desktop								

- **Mixed design: some variables between-subject, others within-subject.**

From [Swan et al. 03]

Types of Statistics

- **Descriptive Statistics**:
  - Describe and explore data
  - All types of graphs and visual representations
  - Summary statistics:
    many numbers $\rightarrow$ few numbers
  - Data analysis begins with descriptive stats
    - Understand data distribution
    - Test assumptions of significance tests

- **Inferential Statistics**:
  - Detect relationships in data
  - Significance tests
  - Infer population characteristics from sample characteristics
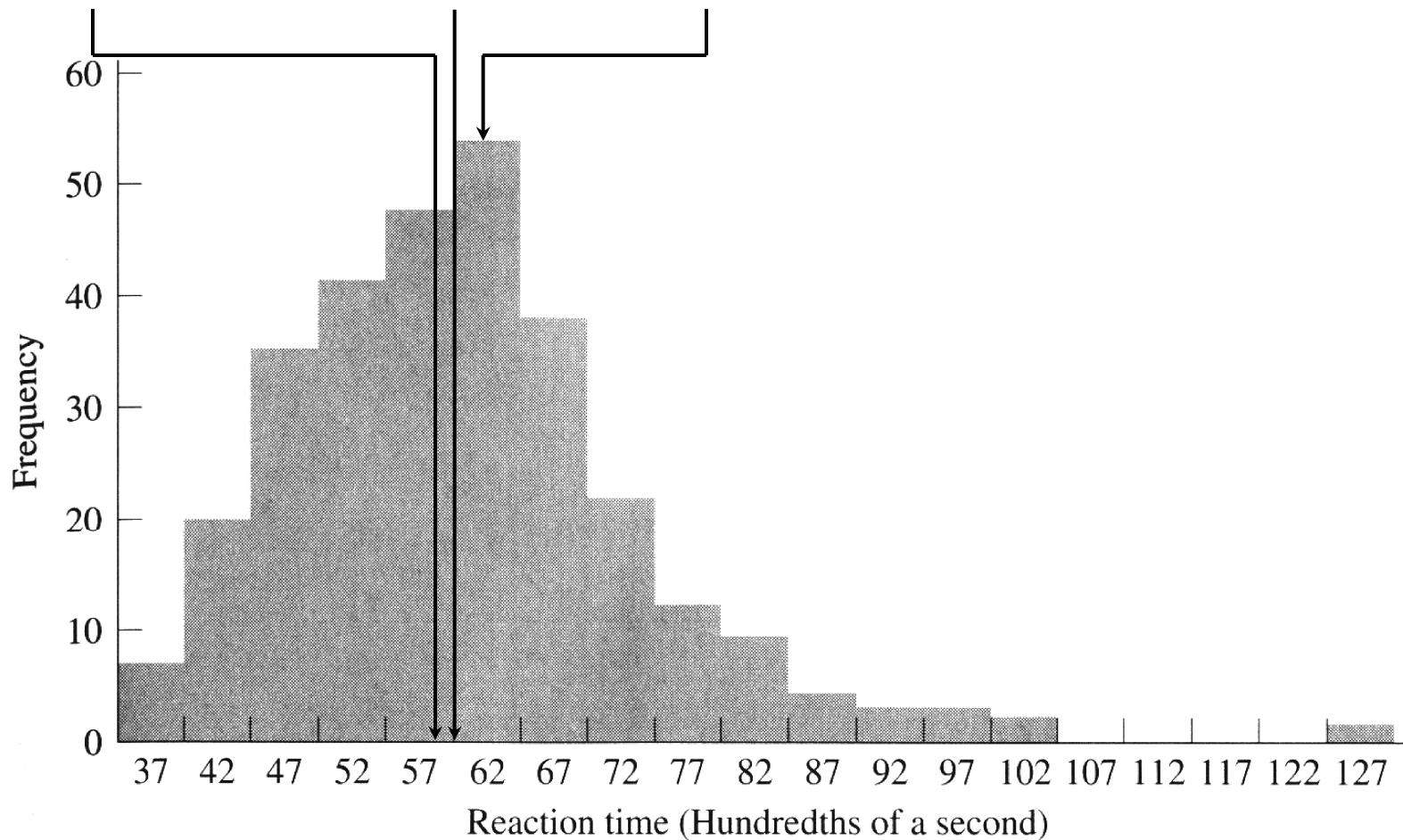
Graphing Data

- **Experimental Validity**

- **Experimental Design**

- *Describing Data*

  – *Graphing Data*

  – **Descriptive Statistics**

- **Inferential Statistics**

  – **Hypothesis Testing**

  – **Analysis of Variance**

  – **Power**

- **Graphical Data Analysis**
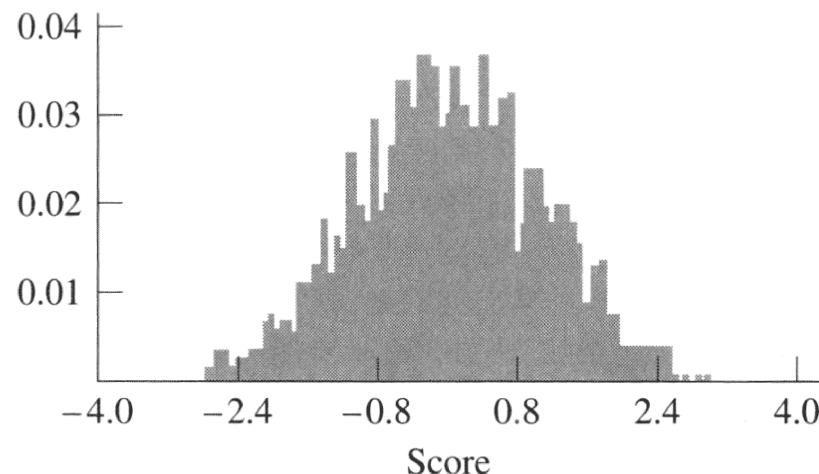
Exploring Data with Graphs

- **Histogram common data overview method**
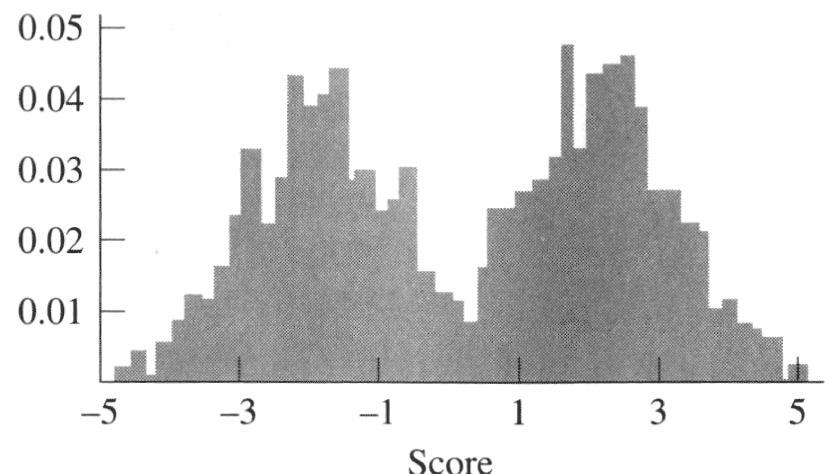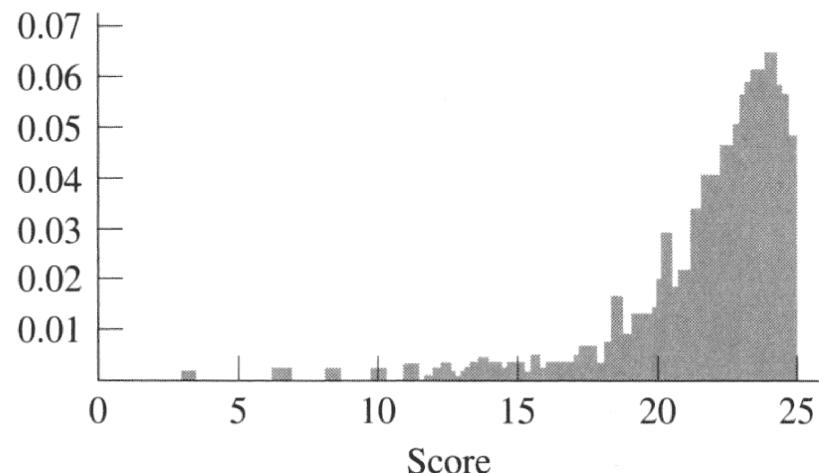
Classifying Data with Histograms
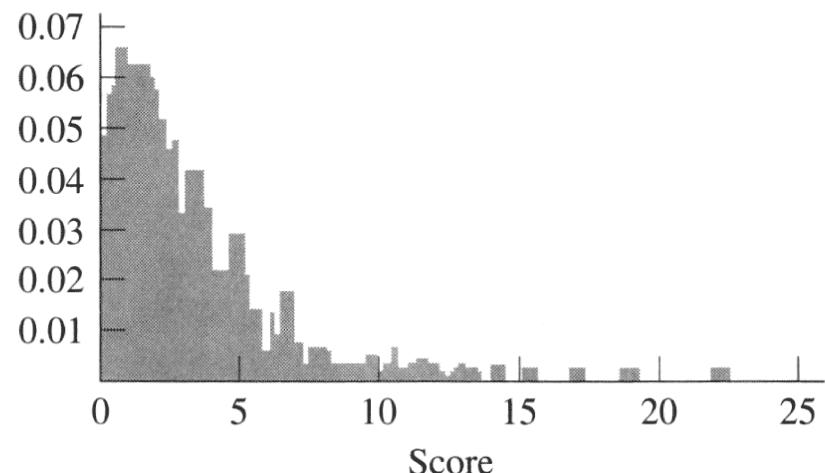
(a) Normal

(b) Bimodal

(c) Negatively skewed

(d) Positively skewed

From [Howell 02] p 28

Stem-and-Leaf:
Histogram From Actual Data

Raw Data	Stem	Leaf
36 37 38 38 39 39 39 40	3s	67
40 40 40 41 41 41 42 42	3.	88999
42 43 43 43 43 43 44 44	4*	0000111
44 44 44 45 45 45 45 45	4t	22233333
45 46 46 46 46 46 46 46	4f	44444555555
46 46 46 46 47 47 47 47	4s	666666666667777777777
47 47 47 47 47 48 48 48	4.	888899999
48 49 49 49 49 49 50 50	5*	00000111111111111
50 50 50 51 51 51 51 51	5t	222222222233333333
51 51 51 51 51 51 51 52	5f	4444445555555
52 52 52 52 52 52 52 52	5s	66666666667777777
52 53 53 53 53 53 53 53	5.	88888888888899999999999
53 54 54 54 54 54 54 55	6*	00000000000011111111111
55 55 55 55 55 55	6t	22222222222223333333333
	6f	444444455555555
	6s	66666666777777777777777
	6.	889999999
	7*	01111
	7t	22222222333
	7f	44444455
	7s	666677
	7.	88899
	8*	00011
	8t	2333
	8f	5
	8s	67
	8.	8
	9*	0
	9t	
	9f	4455
	9s	
	9.	8
	High	104; 104; 125

FIGURE 2.4 *Stem-and-leaf display for reaction time data*

Stem-and-Leaf:
Histogram From Actual Data

Midterm 1
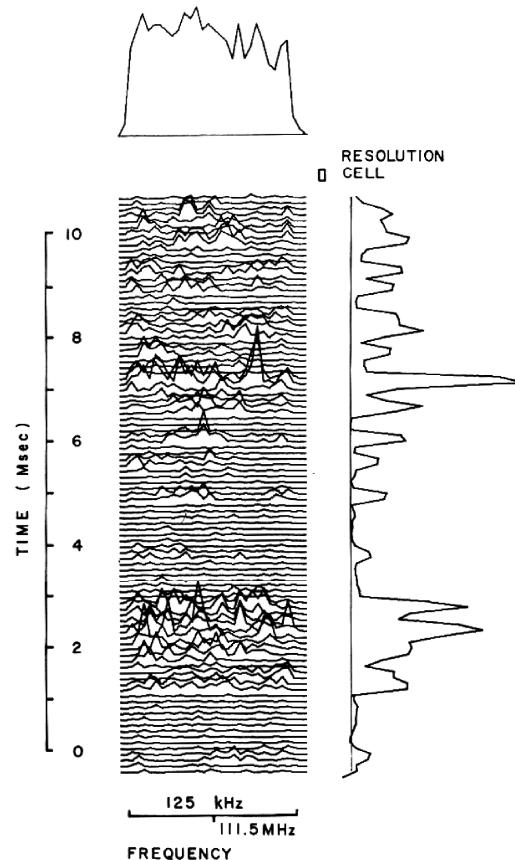
%	Count		
3%	1	0 0	
0%	0	1	
0%	0	2	
0%	0	3	
0%	0	4	
13%	5	5 04689	
8%	3	6 249	F 3%
26%	10	7 0011122568	D 13%
24%	9	8 123334678	C 34%
24%	9	9 002222366	B 24%
3%	1	10 0	A 26%
sum:	38		
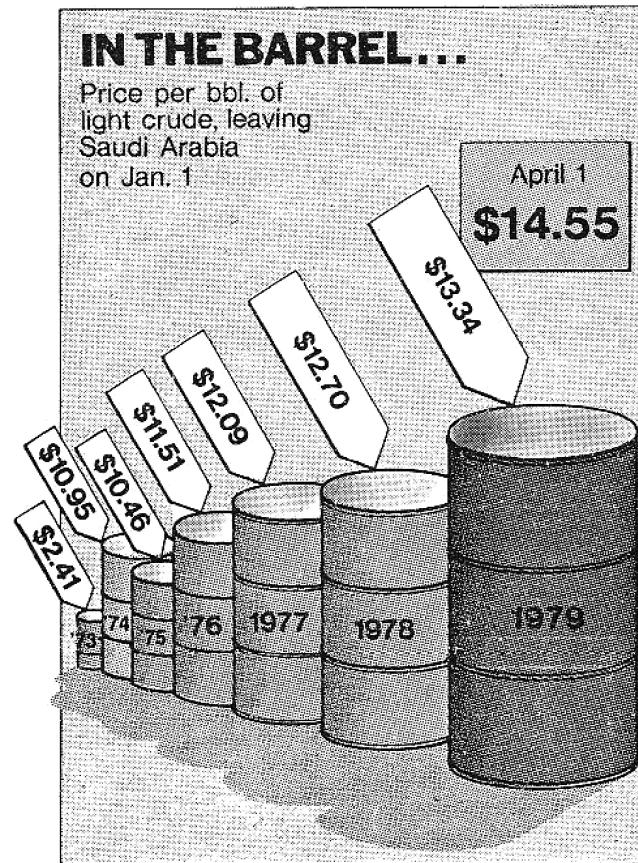
Grades from my fall 2011 Formal Languages class; first midterm

We Have Only Scratched the Surface…

- There are a vary large number of graphing techniques
- Tufte's [83, 90] works are classic, and stat books show many more examples (e.g. Howell [03]).

Lots of good examples…

And plenty of bad examples!

From [Tufte 83], p 134, 62

Descriptive Statistics

- **Experimental Validity**

- **Experimental Design**

- **Describing Data**

  - **Graphing Data**

  - *Descriptive Statistics*

- **Inferential Statistics**

  - **Hypothesis Testing**

  - **Analysis of Variance**

  - **Power**

- **Graphical Data Analysis**

Summary Statistics

- **Many numbers $\rightarrow$ few numbers**

- **Measures of central tendency:**
  - Mean: average
  - Median: middle data value
  - Mode: most common data value

- **Measures of variability / dispersion:**
  - Mean absolute deviation
  - Variance
  - Standard Deviation

Populations and Samples

- **Population:**
  - Set containing every possible element that we want to measure
  - Usually a Platonic, theoretical construct
  - Mean: μ Variance: σ^2 Standard deviation: σ

- **Sample:**
  - Set containing the elements we actually measure (our subjects)
  - Subset of related population
  - Mean: $\overline{X}$ Variance: s^2 Standard deviation: s Number of samples: N

Measuring Variability / Dispersion

Mean:

$$\overline{X} = \frac{\sum X}{N}$$

Mean absolute deviation:

$$\text{m.a.d.} = \frac{\sum \left| X - \overline{X} \right|}{N}$$

Variance:

$$s^2 = \frac{\sum \left(X - \overline{X} \right)^2}{N-1}$$

Standard deviation:

$$s = \sqrt{\frac{\sum \left(X - \overline{X} \right)^2}{N-1}}$$

$$\sigma^2 = \frac{\sum \left(X - \mu \right)^2}{N}$$

- Standard deviation uses same units as samples and mean.
- Calculation of population variance σ^2 is theoretical, because μ almost never known and the population size N would be very large (perhaps infinity).

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Sums of Squares, Degrees of Freedom, Mean Squares

- **Very common terms and concepts**

$$s^2 = \frac{\sum \left(X - \overline{X} \right)^2}{N-1} = \frac{\text{SS}}{df} = \frac{\text{sums of squares}}{\text{degrees of freedom}} = \text{MS (mean squares)}$$

- **Sums of squares:**
  - Summed squared deviations from mean
- **Degrees of freedom:**
  - Given a set of *N* observations used in a calculation, how many numbers in the set may vary
  - Equal to *N* minus number of means calculated
- **Mean squares:**
  - Sums of squares divided by degrees of freedom
  - Another term for variance, used in ANOVA

Example: Degrees of Freedom
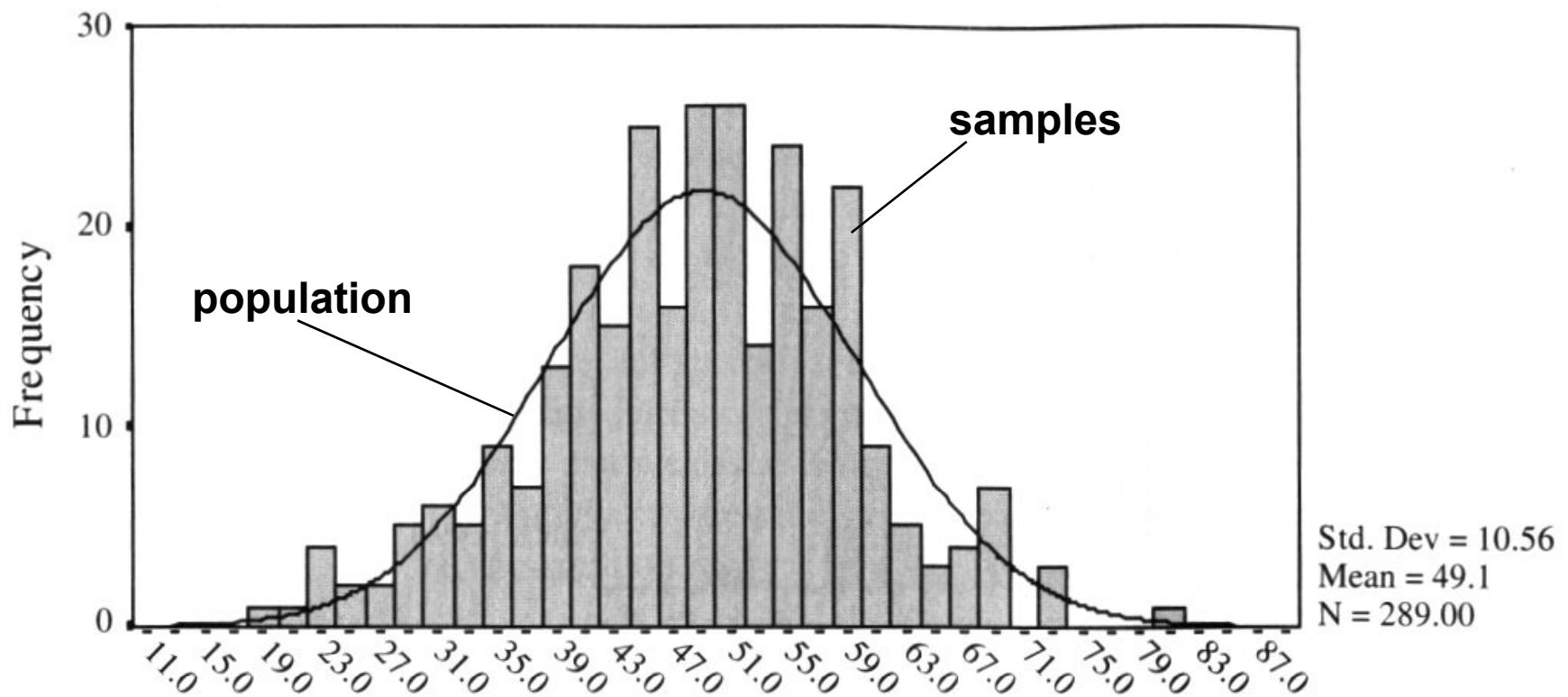
- **Samples: {6, 8, 10}; $N = 3$; $X = 8$**

- **If mean must remain $X = 8$;
  how many numbers may vary?**

- **Answer: 2 may vary**
  - **Example: let 6→4, 8→14, then $(4 + 14 + a)/3 = 8$**
  - **$a = 6$ if $X = 8$; value of a is constrained**

- **We say that set {6, 8, 10} has
  $N - 1 = 2$ degrees of freedom (*dof*, *df*)**
  - **Generally equal to N minus 1 per mean calculated**

Hypothesis Testing

- **Experimental Validity**

- **Experimental Design**

- **Describing Data**

  – **Graphing Data**

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- *Inferential Statistics*

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Hypothesis Testing

- **Goal is to infer population characteristics from sample characteristics**

Std. Dev = 10.56
Mean = 49.1
N = 289.00

From [Howell 02], p 78

Testable Hypothesis
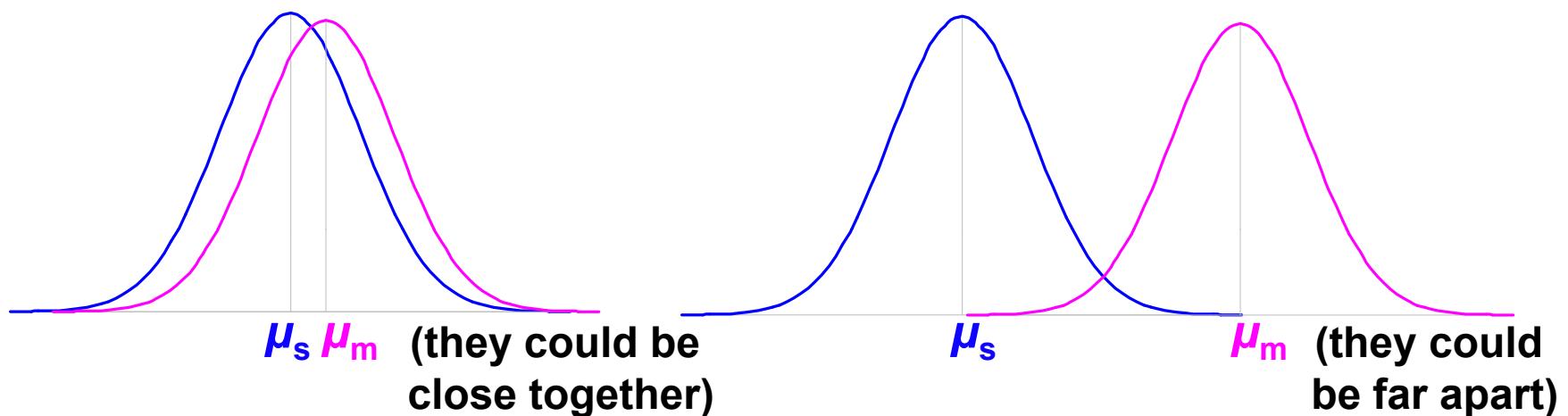
- **General hypothesis: The research question that motivates the experiment.**

- **Testable hypothesis: The research question expressed in a way that can be measured and studied.**

- **Generating a good testable hypothesis is a real skill of experimental design.**
  - By *good*, we mean contributes to experimental validity.
  - Skill best learned by studying and critiquing previous experiments.

Testable Hypothesis Example
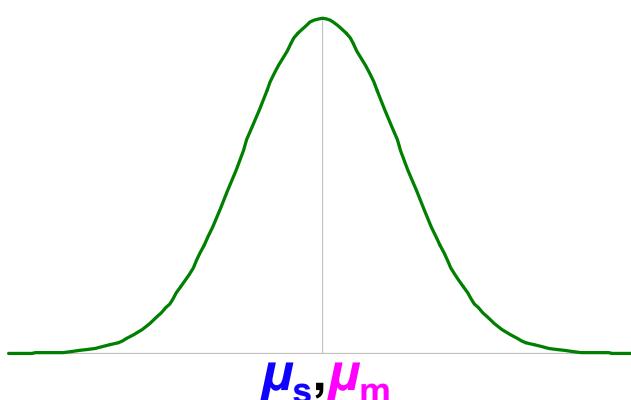
- **General hypothesis**: Stereo will make people more effective when navigating through a virtual environment (VE).

- **Testable hypothesis**: We measure time it takes for subjects to navigate through a particular VE, under conditions of stereo and mono viewing. We hypothesis subjects will be faster under stereo viewing.

- Testable hypothesis requires a measurable quantity:
    - Time, task completion counts, error counts, etc.

- Some factors effecting experimental validity:
    - Is VE representative of something interesting (e.g., a real-world situation)?
    - Is navigation task representative of something interesting?
    - Is there an underlying theory of human performance that can help predict the results? Could our results contribute to this theory?

What Are the Possible Alternatives?

- **Let time to navigate be μ_s: stereo time; μ_m: mono time**
  - Perhaps there are two populations: $\mu_s - \mu_m = d$

$\mu_s\ \mu_m$ (they could be close together)

μ_s μ_m (they could be far apart)

  - Perhaps there is one population: $\mu_s - \mu_m = 0$

μ_s, μ_m

Hypothesis Testing Procedure

1. Develop testable hypothesis H_1: $\mu_s - \mu_m = d$
   - (E.g., subjects faster under stereo viewing)

2. Develop null hypothesis H_0: $\mu_s - \mu_m = 0$
   - Logical opposite of testable hypothesis

3. Construct sampling distribution assuming H_0 is true.

4. Run an experiment and collect samples; yielding sampling statistic X.
   - (E.g., measure subjects under stereo and mono conditions)

5. Referring to sampling distribution, calculate conditional probability of seeing X given H_0: $p(X | H_0)$.
   - If probability is low ($p \leq 0.05$, $p \leq 0.01$), we are unlikely to see X when H_0 is true. We reject H_0, and embrace H_1.
   - If probability is not low ($p > 0.05$), we are likely to see X when H_0 is true. We do not reject H_0.

Example 1: VE Navigation with Stereo Viewing

1. **Hypothesis** H_1: $\mu_s - \mu_m = d$
   - Subjects faster under stereo viewing.

2. **Null hypothesis** H_0: $\mu_s - \mu_m = 0$
   - Subjects same speed whether stereo or mono viewing.

3. **Constructed sampling distribution assuming H_0 is true.**

4. **Ran an experiment and collected samples:**
   - 32 subjects, collected 128 samples
   - X_s = 36.431 sec; X_m = 34.449 sec; $X_s - X_m$ = 1.983 sec

5. **Calculated conditional probability of seeing 1.983 sec given H_0: $p($ 1.983 sec $| H_0) = 0.445$.**
   - $p = 0.445$ not low, we are likely to see 1.983 sec when H_0 is true. We do not reject H_0.
   - This experiment did not tell us that subjects were faster under stereo viewing.

Example 2: Effect of Intensity on AR Occluded Layer Perception

1. **Hypothesis H_1: $\mu_c - \mu_d = d$**
   - Tested constant and decreasing intensity. Subjects faster under decreasing intensity.

2. **Null hypothesis H_0: $\mu_c - \mu_d = 0$**
   - Subjects same speed whether constant or decreasing intensity.

3. **Constructed sampling distribution assuming H_0 is true.**

4. **Ran an experiment and collected samples:**
   - 8 subjects, collected 1728 samples
   - X_c = 2592.4 msec; X_d = 2339.9 msec; $X_c - X_d$ = 252.5 msec

5. **Calculated conditional probability of seeing 252.5 msec given H_0: $p(\,252.5\text{ msec} \mid H_0\,) = 0.008$.**
   - $p = 0.008$ is low ($p \leq 0.01$); we are unlikely to see 252.5 msec when H_0 is true. We reject H_0, and embrace H_1.
   - This experiment suggests that subjects are faster under decreasing intensity.

Some Considerations…

- **The conditional probability $p(X|H_0)$**
  - Much of statistics involves how to calculate this probability; source of most of statistic's complexity
  - Logic of hypothesis testing the same regardless of how $p(X|H_0)$ is calculated
  - If you can calculate $p(X|H_0)$, you can test a hypothesis

- **The null hypothesis H_0**
  - H_0 usually in form $f(\mu_1, \mu_2, \ldots) = 0$
  - Gives hypothesis testing a double-negative logic: assume H_0 as the opposite of H_1, then reject H_0
  - Philosophy is that can never prove something true, but can prove it false
  - H_1 usually in form $f(\mu_1, \mu_2, \ldots) \neq 0$; we don't know what value it will take, but main interest is that it is not 0

When We Reject H_0

- **Calculate $\alpha = p(X \mid H_0)$, when do we reject H_0?**
  - In psychology, two levels: $\alpha \leq 0.05$; $\alpha \leq 0.01$
  - Other fields have different values

- **What can we say when we reject H_0 at $\alpha = 0.008$?**
  - "If H_0 is true, there is only an 0.008 probability of getting our results, and this is unlikely."
    - **Correct**!

  - "There is only a 0.008 probability that our result is in error."
    - **Wrong**, this statement refers to $p(H_0)$, but that's not what we calculated.

  - "There is only a 0.008 probability that H_0 could have been true in this experiment."
    - **Wrong**, this statement refers to $p(H_0 \mid X)$, but that's not what we calculated.

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When We Don't Reject H_0

- **What can we say when we don't reject H_0 at $\alpha = 0.445$?**
  - "We have proved that H_0 is true."
  - "Our experiment indicates that H_0 is true."
    - **Wrong**, statisticians agree that hypothesis testing cannot prove H_0 is true.

- **Statisticians do not agree on what failing to reject H_0 means.**
  - **Conservative viewpoint (Fisher):**
    - We must suspend judgment, and cannot say anything about the truth of H_0.
  - **Alternative viewpoint (Neyman & Pearson):**
    - We "accept" H_0, and act as if it's true for now…
    - But future data may cause us to change our mind

Probabilistic Reasoning

- **If hypothesis testing was absolute:**
  - If H_0 is true, then *X* cannot occur…however, *X* has occurred…therefore H_0 is false.

  - e.g.: If a person is a Martian, then they are not a member of Congress (true)…this person is a member of Congress…therefore they are not a Martian. (correct result)

  - e.g.: If a person is an American, then they are not a member of Congress (false)…this person is a member of Congress…therefore they are not an American. (incorrect result, but correct logical reasoning)

p	q	$p \rightarrow q$	$\neg q \rightarrow \neg p$
T	T	T	T
T	F	F	F
F	T	T	T
F	F	T	T

$$\begin{array}{l} p \rightarrow q \\ \neg q \\ \hline \rightarrow \neg p \end{array} \right\} \text{modus tollens}$$

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Probabilistic Reasoning

- **However, hypothesis testing is probabilistic:**
  - If H_0 is true, then *X* is highly unlikely…however, *X* has occurred…therefore H_0 is highly unlikely.

  - e.g.: If a person is an American, then they are probably not a member of Congress (true, right?)…this person is a member of Congress…therefore they are probably not an American.
    (incorrect result, but correct hypothesis testing reasoning)

p	q	$p \rightarrow q$	$\neg q \rightarrow \neg p$
T	T	T	T
T	F	F	F
F	T	T	T
F	F	T	T

$$p \rightarrow q$$
$$\neg q$$
$$\rule{3cm}{0.4pt}$$
$$\rightarrow \neg p$$

modus tollens

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Hypothesis Testing Outcomes

		Decision	
		Reject H_0	**Don't reject H_0**
True state of the world	H_0 **false**	**correct a result!** $p = 1 - \beta$ = **power**	**wrong type II error** $p = \beta$
	H_0 **true**	**wrong type I error** $p = \alpha$	**correct (but wasted time)** $p = 1 - \alpha$

- $p(X \mid H_0)$ compared to α, so hypothesis testing involves setting α (typically 0.05 or 0.01)
- Two ways to be right:
  - Find a result
  - Fail to find a result and waste time running an experiment
- Two ways to be wrong:
  - **Type I error**: we think we have a result, but we are wrong
  - **Type II error**: a result was there, but we missed it

When Do We *Really* Believe a Result?

- **When we reject H_0, we have a result, but:**
  - It's possible we made a type I error
  - It's possible our finding is not reliable
    - Just an artifact of our particular experiment

- **So when do we *really* believe a result?**
  - **Statistical evidence**
    - α level: ($p < .05$, $p < .01$, $p < .001$)
    - Power

  - **Meta-statistical evidence**
    - Plausible explanation of observed phenomena
      - Based on theories of human behavior: perceptual, cognitive psychology; control theory, etc.
    - Repeated results
      - Especially by others
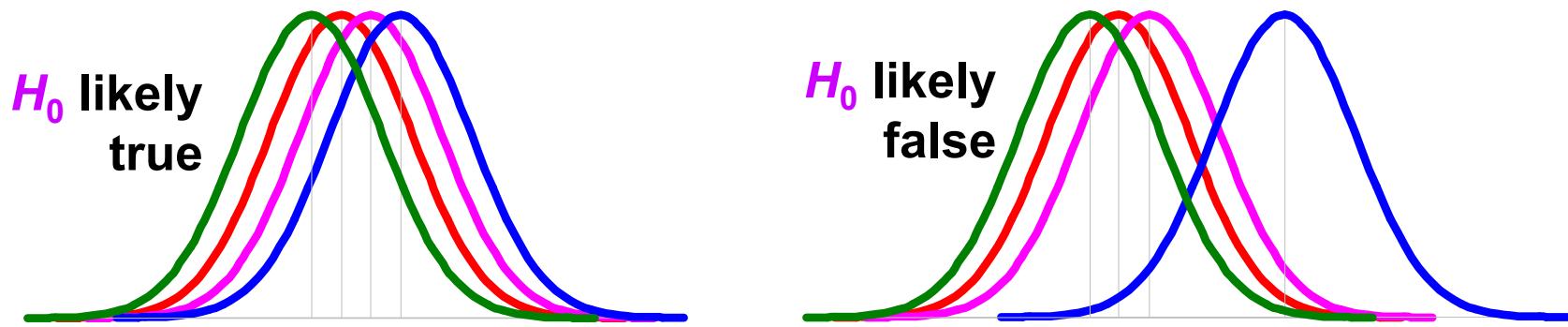
Analysis of Variance

- **Experimental Validity**

- **Experimental Design**

- **Describing Data**

  – **Graphing Data**

  – **Descriptive Statistics**

- **Inferential Statistics**

  – **Hypothesis Testing**

  – *Analysis of Variance*

  – **Power**

- **Graphical Data Analysis**

ANOVA: Analysis of Variance

- *t*-test used for comparing two means
  - (**2 x 1** designs)

- **ANOVA used for factorial designs**
  - Comparing multiple levels (*n* **x 1** designs)
  - Comparing multiple independent variables
    (*n* **x** *m*, *n* **x** *m* **x** *p*), etc.
  - Can also compare two levels (**2 x 1** designs);
    ANOVA can be considered a generalization of a *t*-test

- **No limit to experimental design size or complexity**

- **Most widely used statistical test in psychological research**

- **ANOVA based on the *F* distribution;
  also called an *F*-Test**

How ANOVA Works

H_0 likely true

H_0 likely false
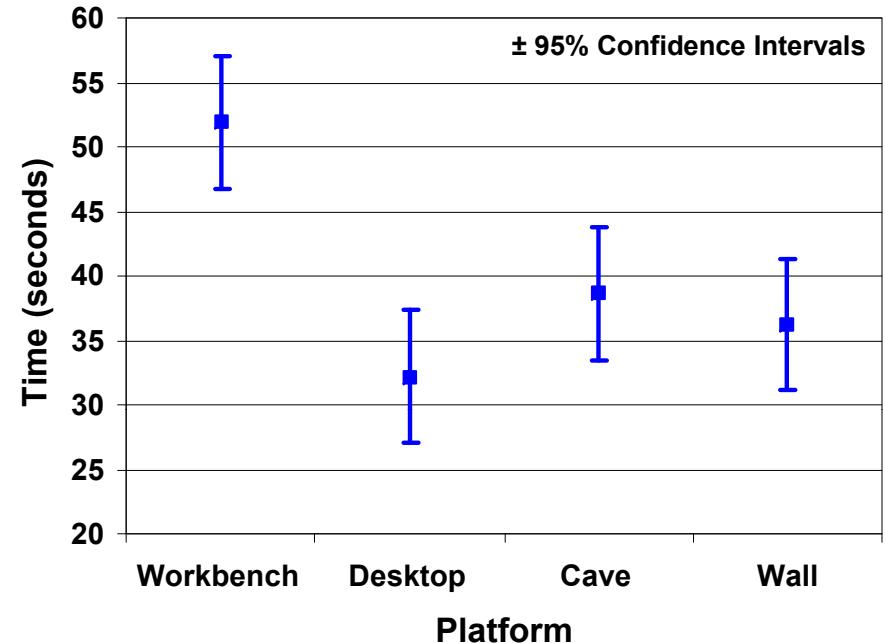
- Null hypothesis H_0: $\mu_1 = \mu_2 = \mu_3 = \mu_4$; H_1: at least one mean differs
- Estimate variance between each group: $MS_{between}$
  - Based on the difference between group means
  - If H_0 is true, accurate estimation
  - If H_0 is false, biased estimation: overestimates variance
- Estimate variance within each group: MS_{within}
  - Treats each group separately
  - Accurate estimation whether H_0 is true or false
- Calculate F critical value from ratio: $F = MS_{between} / MS_{within}$
  - If $F \approx 1$, then accept H_0
  - If $F \gg 1$, then reject H_0

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ANOVA Example

- **Hypothesis H_1:**
  - Platform (Workbench, Desktop, Cave, or Wall) will affect user navigation time in a virtual environment.

- **Null hypothesis H_0: $\mu_b = \mu_d = \mu_c = \mu_w$.**
  - Platform will have no effect on user navigation time.

- **Ran 32 subjects, each subject used each platform, collected 128 data points.**

± 95% Confidence Intervals

Source	SS	df	MS	F	p
Between (platform)	1205.8876	3	401.9625	3.100*	0.031
Within (P x S)	12059.0950	93	129.6677		
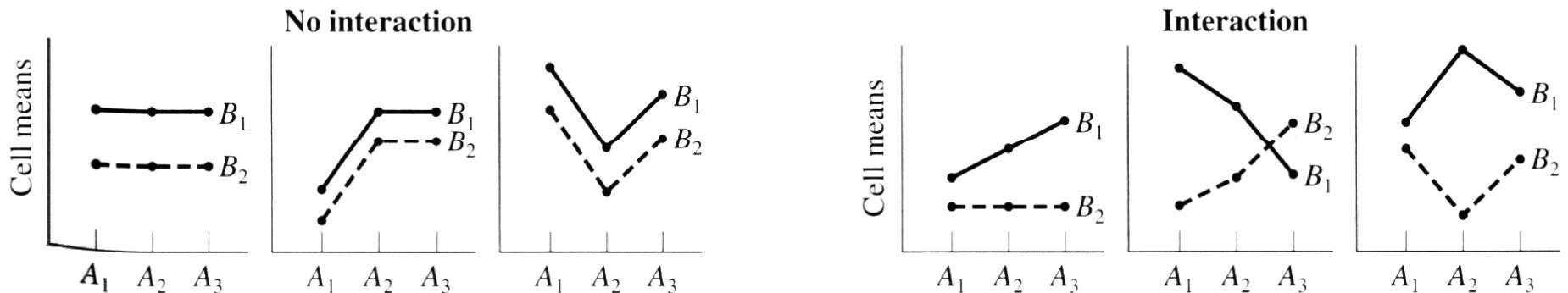
*$p < .05$

- **Reporting in a paper: $F(3, 93) = 3.1$, $p < .05$**

Data from [Swan et al 03], calculations shown in [Howell 02], p 471

Main Effects and Interactions
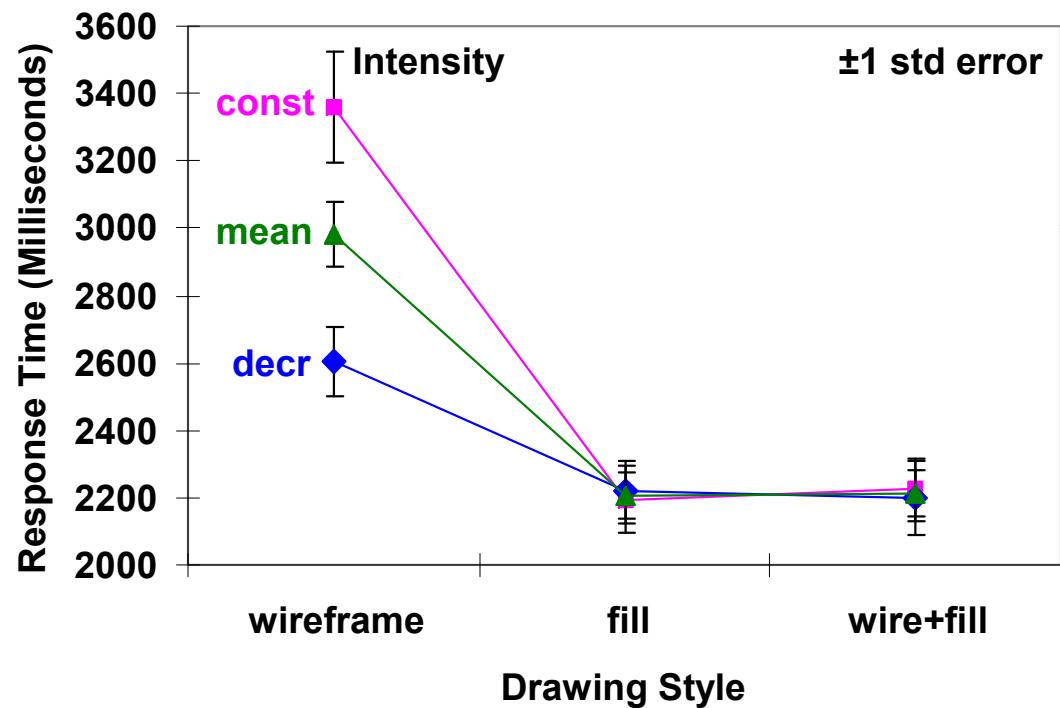
- **Main Effect**
  - **The effect of a single independent variable**
  - **In previous example, a *main effect* of platform on user navigation time: users were slower on the Workbench, relative to other platforms**

- **Interaction**
  - **Two or more variables interact**
  - **Often, a 2-way interaction can describe main effects**

No interaction / Interaction

From [Howell 02], p 431

Example of an Interaction

- **Main effect of drawing style:**
  - $F(2,14) = 8.84$, $p < .01$
  - Subjects slower with wireframe style

- **Main effect of intensity:**
  - $F(1,7) = 13.16$, $p < .01$
  - Subjects faster with decreasing intensity

- **Interaction between drawing style and intensity:**
  - $F(2,14) = 9.38$, $p < .01$
  - The effect of decreasing intensity occurs only for the wireframe drawing style; for fill and wire+fill, intensity had no effect
  - This completely describes the main effects discussed above

Data from [Living Swan et al 03]
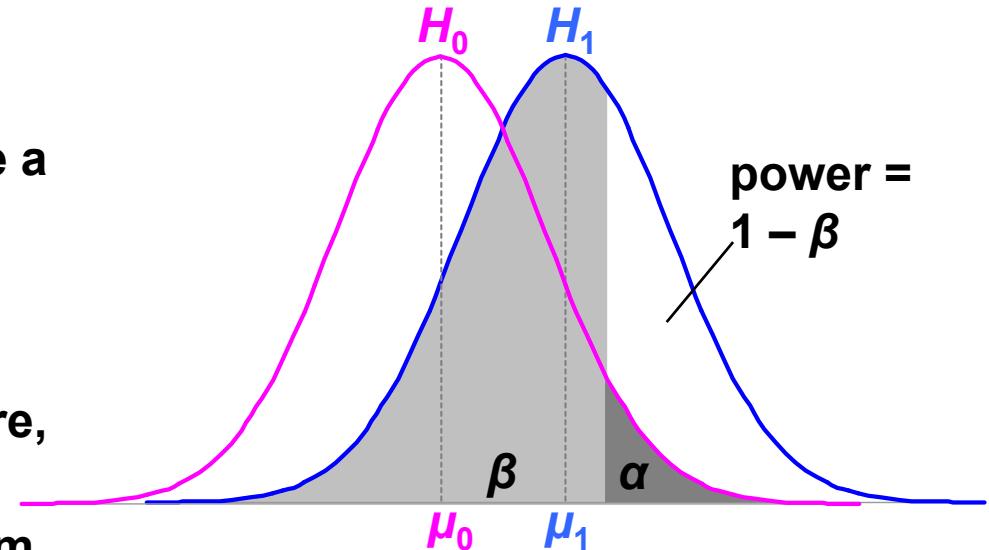
Power

- **Experimental Validity**

- **Experimental Design**

- **Describing Data**

  - **Graphing Data**

  - **Descriptive Statistics**

- **Inferential Statistics**

  - **Hypothesis Testing**

  - **Analysis of Variance**

  - *Power*

- **Graphical Data Analysis**

Interpreting α, β, and Power
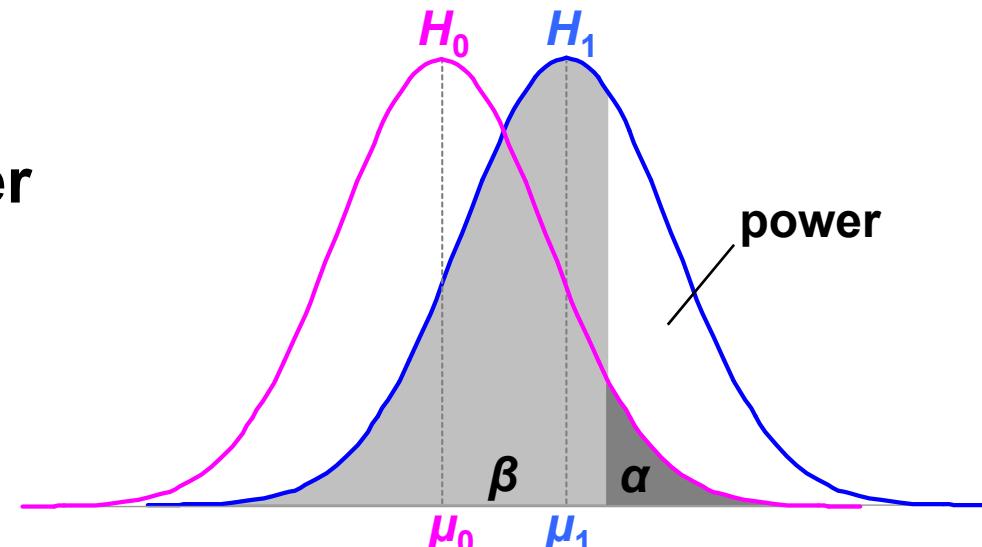
		Decision	
		Reject H_0	Don't reject H_0
True state of the world	H_0 **false**	a result! $p = 1 - \beta$ = power	type II error $p = \beta$
	H_0 **true**	type I error $p = \alpha$	wasted time $p = 1 - \alpha$

- **If H_0 is true:**
  - α is probability we make a type I error: we think we have a result, but we are wrong

- **If H_1 is true:**
  - β is probability we make a type II error: a result was there, but we missed it
  - Power is a more common term than β

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Increasing Power by Increasing α

- **Illustrates α / power tradeoff**
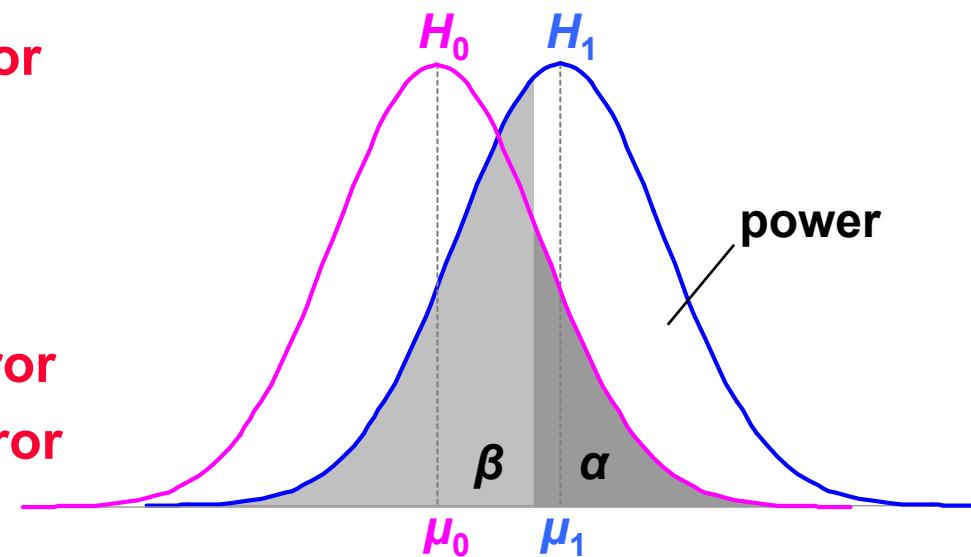
- **Increasing α:**
  - Increases power
  - Decreases type II error
  - Increases type I error
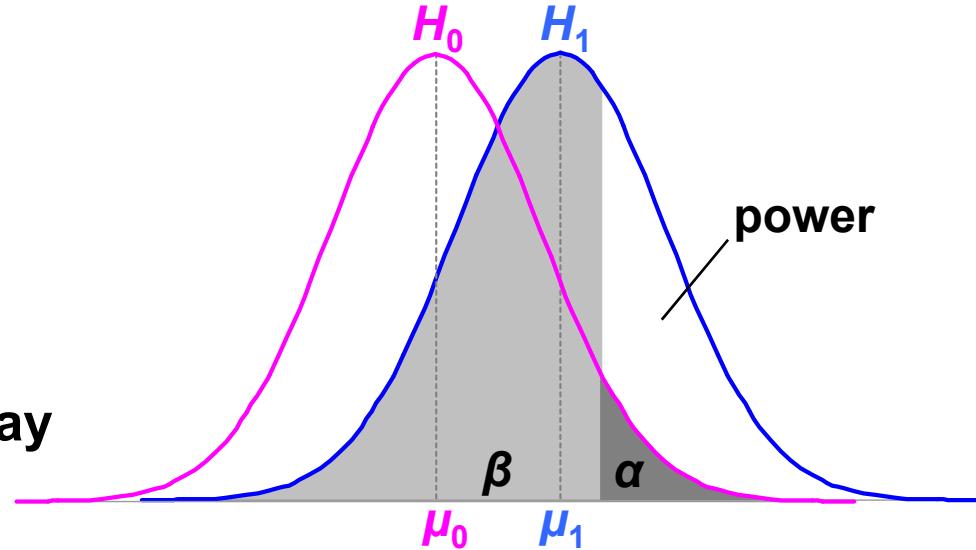
- **Decreasing α:**
  - Decreases power
  - Increases type II error
  - Decreases type I error

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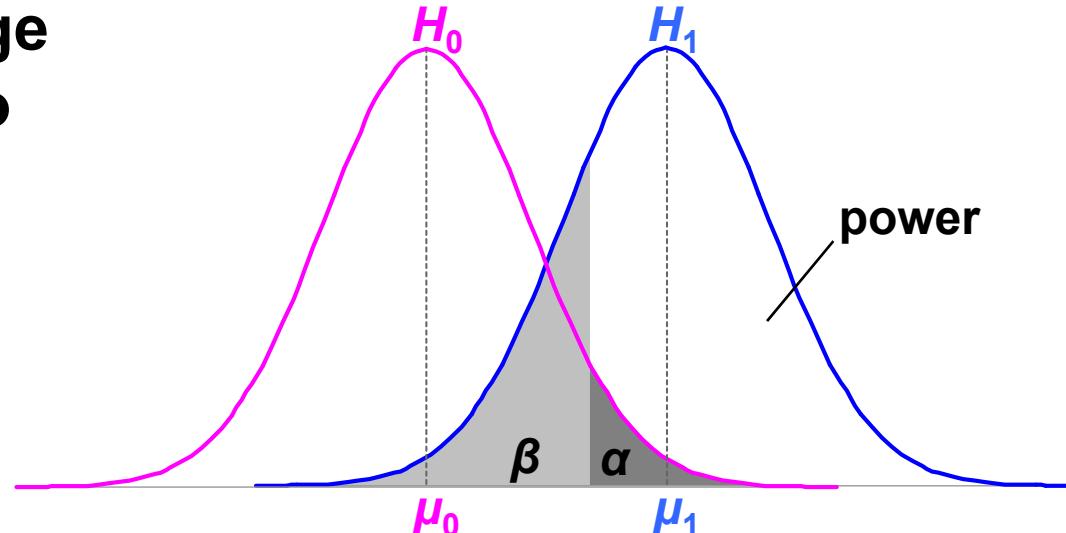
Increasing Power by Measuring a Bigger Effect
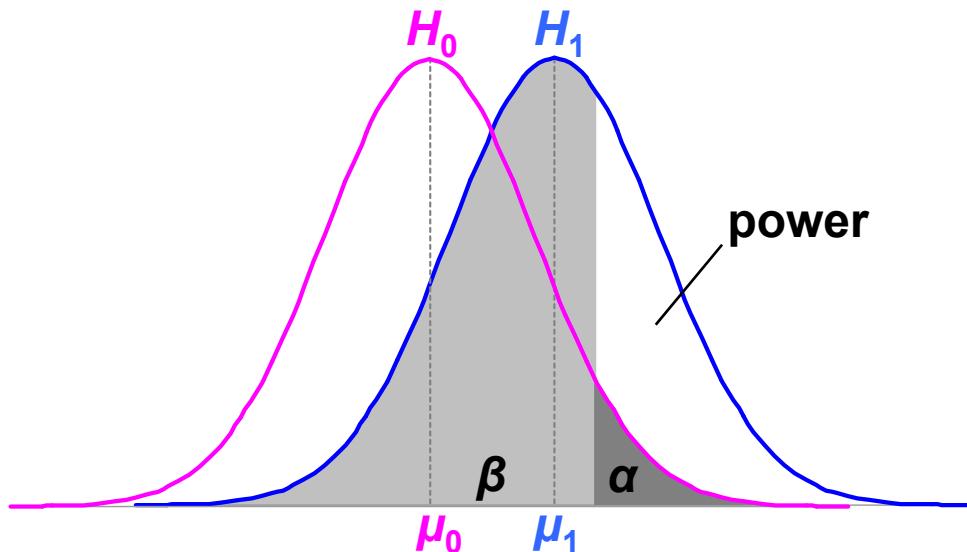
- **If the effect size is large:**
  - Power increases
  - Type II error decreases
  - α and type I error stay the same
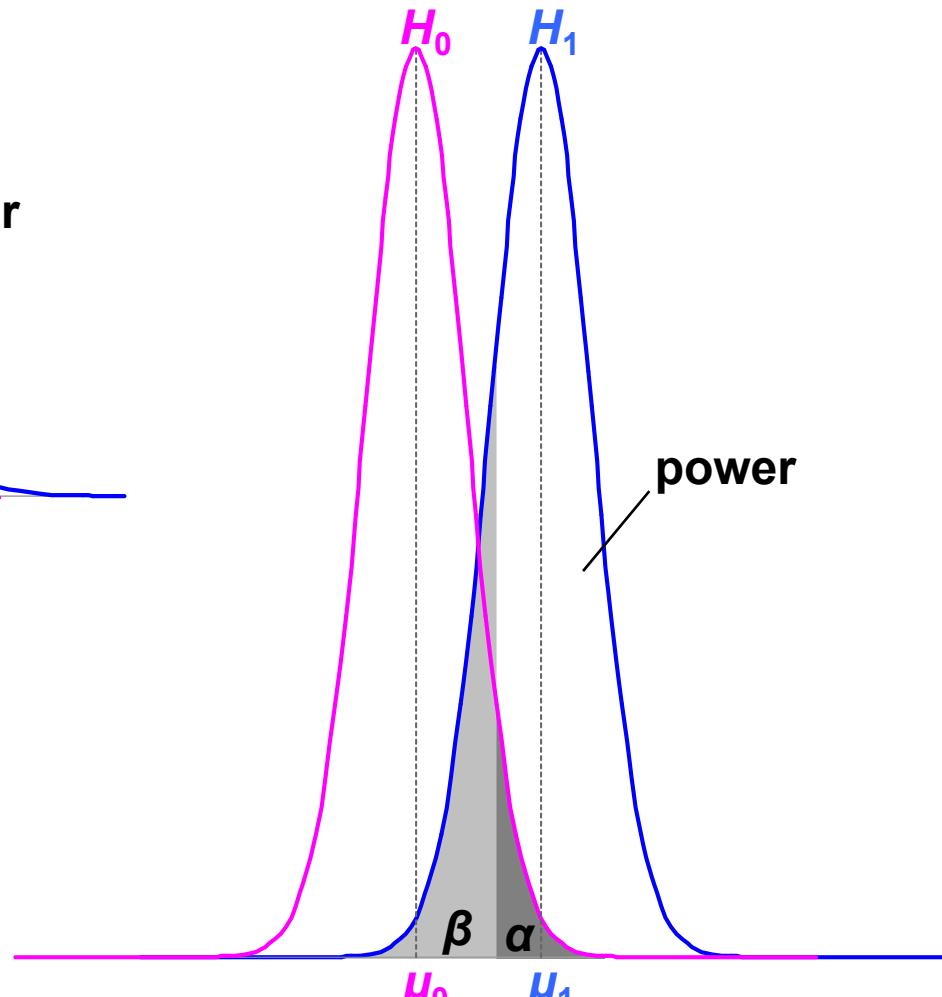
- **Unsurprisingly, large effects are easier to detect than small effects**

Increasing Power by Collecting More Data
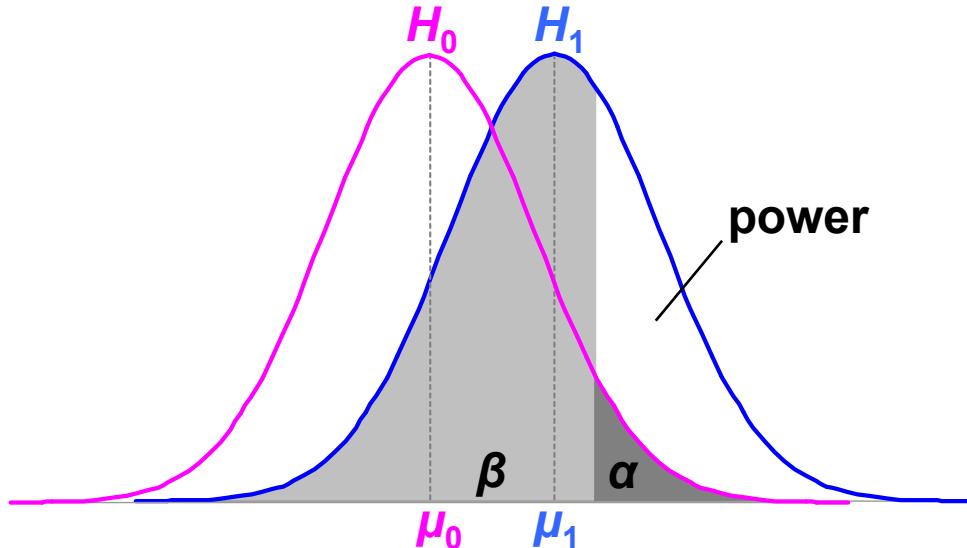
- **Increasing sample size (N):**
  - Decreases variance
  - Increases power
  - Decreases type II error
  - α and type I error stay the same
- **There are techniques that give the value of N required for a certain power level.**
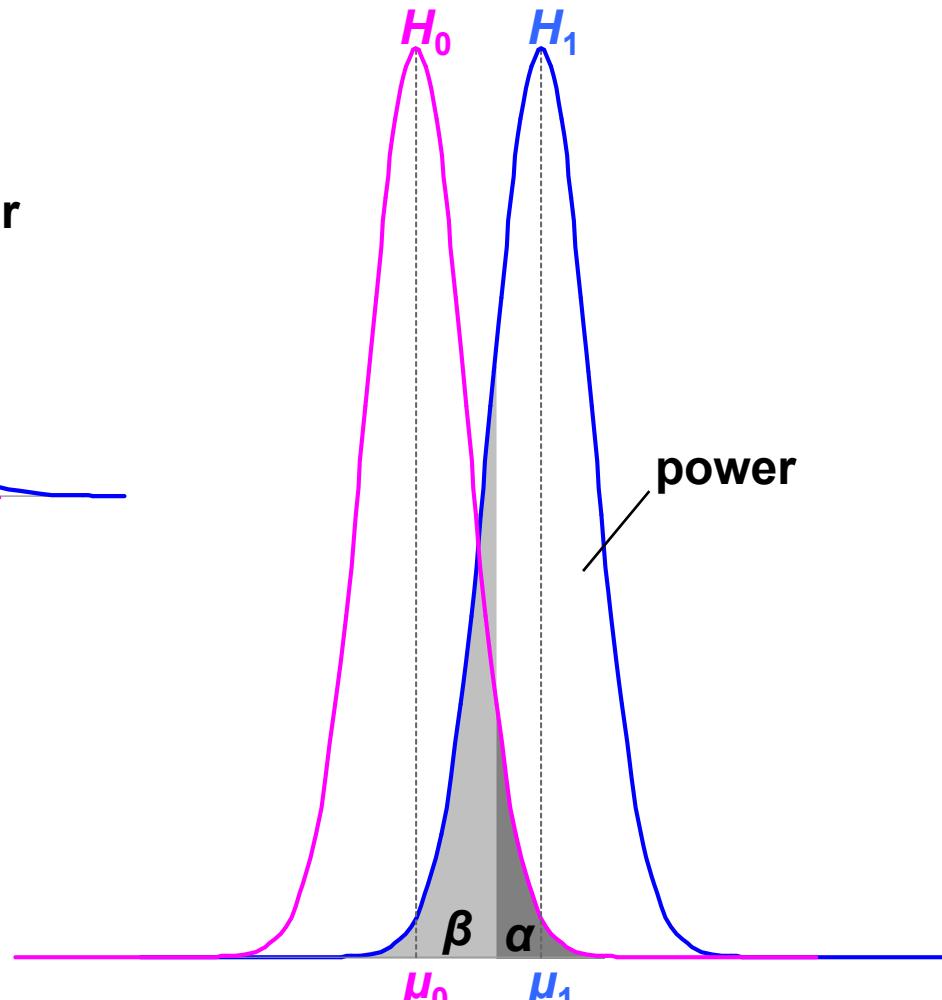
- Here, effect size remains the same, but variance drops by half.

Increasing Power by Decreasing Noise

- **Decreasing experimental noise:**
  - Decreases variance
  - Increases power
  - Decreases type II error
  - α and type I error stay the same
- **More careful experimental results give lower noise.**

- **Here, effect size remains the same, but variance drops by half.**

Using Power

- **Need α, effect size, and sample size for power:**

$$\text{power} = f(\ \alpha,\ |\mu_0 - \mu_1|,\ N\ )$$

- **Problem for VR / AR:**
  - **Effect size $|\mu_0 - \mu_1|$ hard to know in our field**
    - Population parameters estimated from prior studies
    - But our field is so new, not many prior studies
  - **Can find effect sizes in more mature fields**

- **Post-hoc power analysis:**

$$\text{effect size} = |X_0 - X_1|$$

  - Estimate from sample statistics
  - But this makes statisticians grumble (e.g. [Howell 02] [Cohen 88])
  - Same information as *p* value

Other Uses for Power

1. **Number samples needed for certain power level:**

    $N = f(\text{power}, \alpha, |\mu_0 - \mu_1| \text{ or } |X_0 - X_1|)$

    - Number extra samples needed for more powerful result
    - Gives "rational basis" for deciding N [Cohen 88]

2. **Effect size that will be detectable:**

 $|\mu_0 - \mu_1| = f(N, \text{power}, \alpha)$
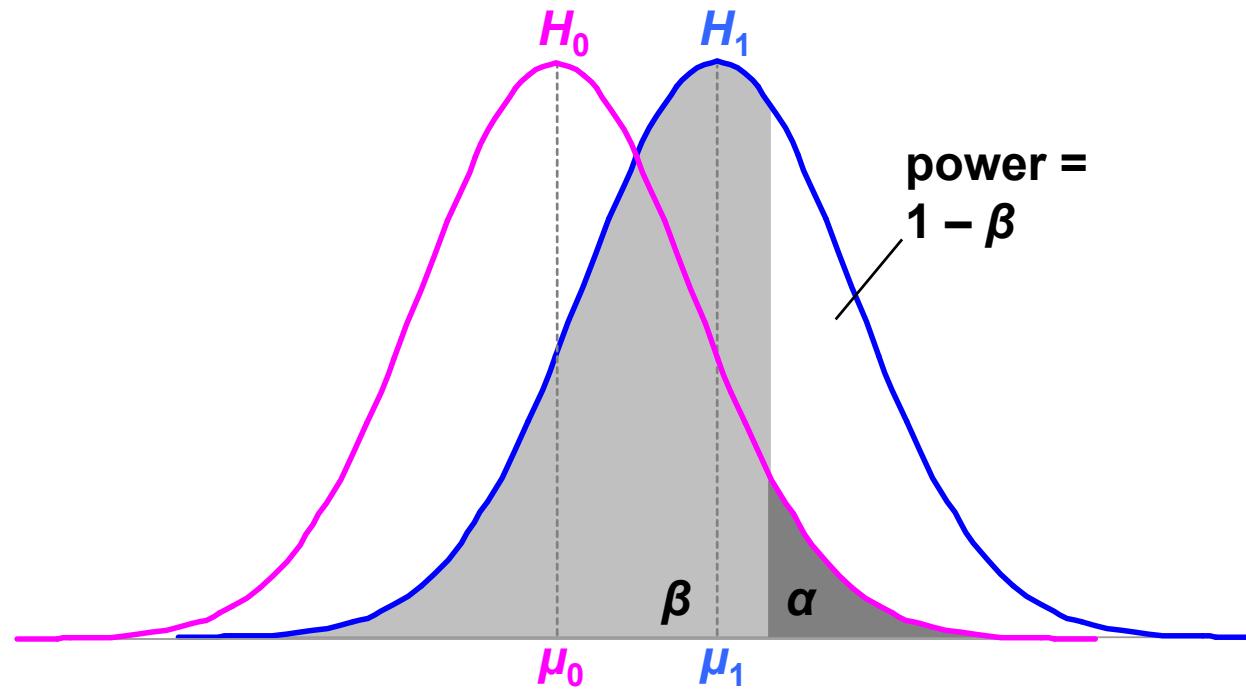
3. **Significance level needed:**

    $\alpha = f(|\mu_0 - \mu_1| \text{ or } |X_0 - X_1|, N, \text{power})$

(1) is the most common power usage

Arguing the Null Hypothesis

- **Cannot directly argue H_0: $\mu_s - \mu_m = 0$. But we can argue that $|\mu_0 - \mu_1| < d$.**
  - Thus, we have bound our effect size by d.
 - If d is *small*, effectively argued null hypothesis.

H_0 H_1

power =
$1 - \beta$

β α

μ_0 μ_1

From [Cohen 88], p 16

Graphical Data Analysis
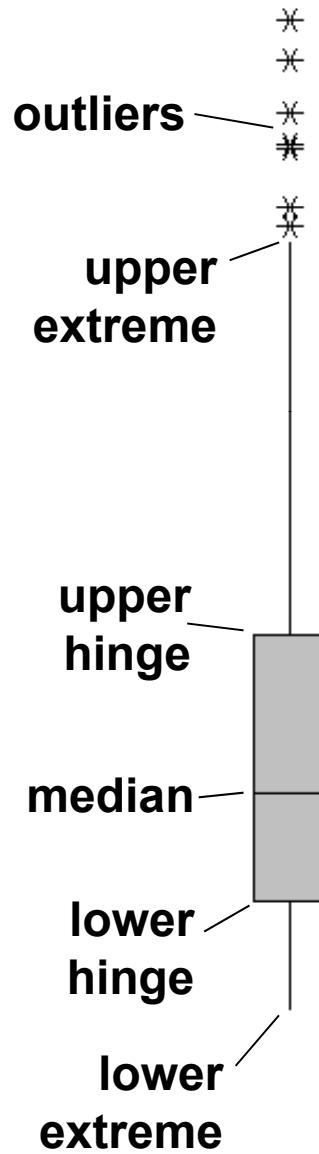
- **Experimental Validity**

- **Experimental Design**

- **Describing Data**

  - **Graphing Data**

  - **Descriptive Statistics**

- **Inferential Statistics**

  - **Hypothesis Testing**

  - **Analysis of Variance and Factorial Experiments**

  - **Power**

- *Graphical Data Analysis*

Exploratory Data Analysis (EDA)
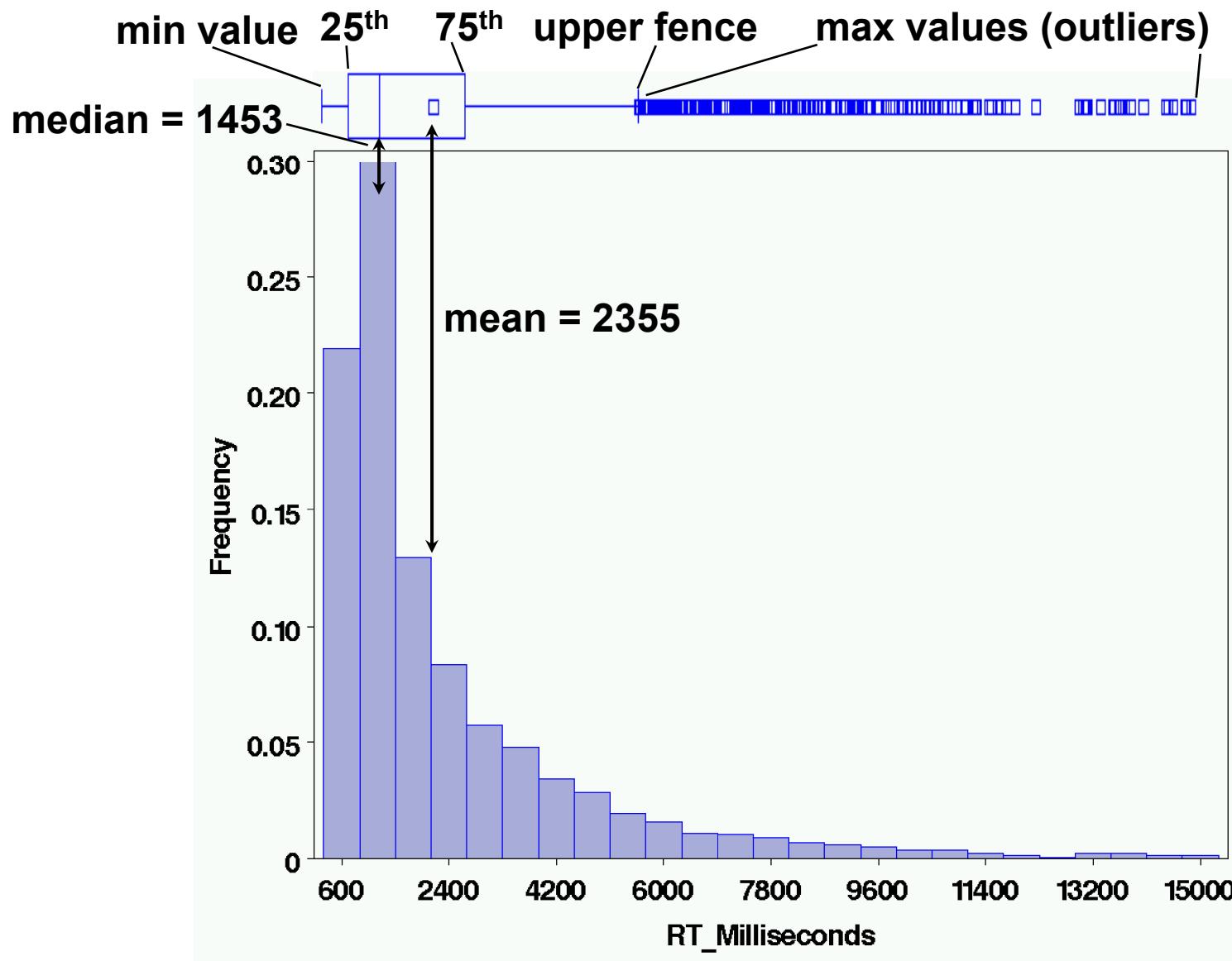
- **EDA is:**
  - A set of **data analysis tools** and **techniques**
  - A **philosophy** of how to investigate data

- **EDA philosophy: data should be explored, with an open mind**
  - Contrary to then-popular view: statistical tests should be planned before data collected
  - Data may reveal **more** than anticipated, **other** than anticipated
  - Emphasizes **images** that yield rapid insight
  - Greatest value "when it forces us to notice what we never expected to see." [Tukey 77]

- **EDA workflow:**
  - **1st**: explore the data (descriptive statistics)
  - **2nd**: confirm the findings (hypothesis testing)

- **EDA is visualization philosophy applied to data analysis**

From [Smith Prentice 93]

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EDA and Median Statistics
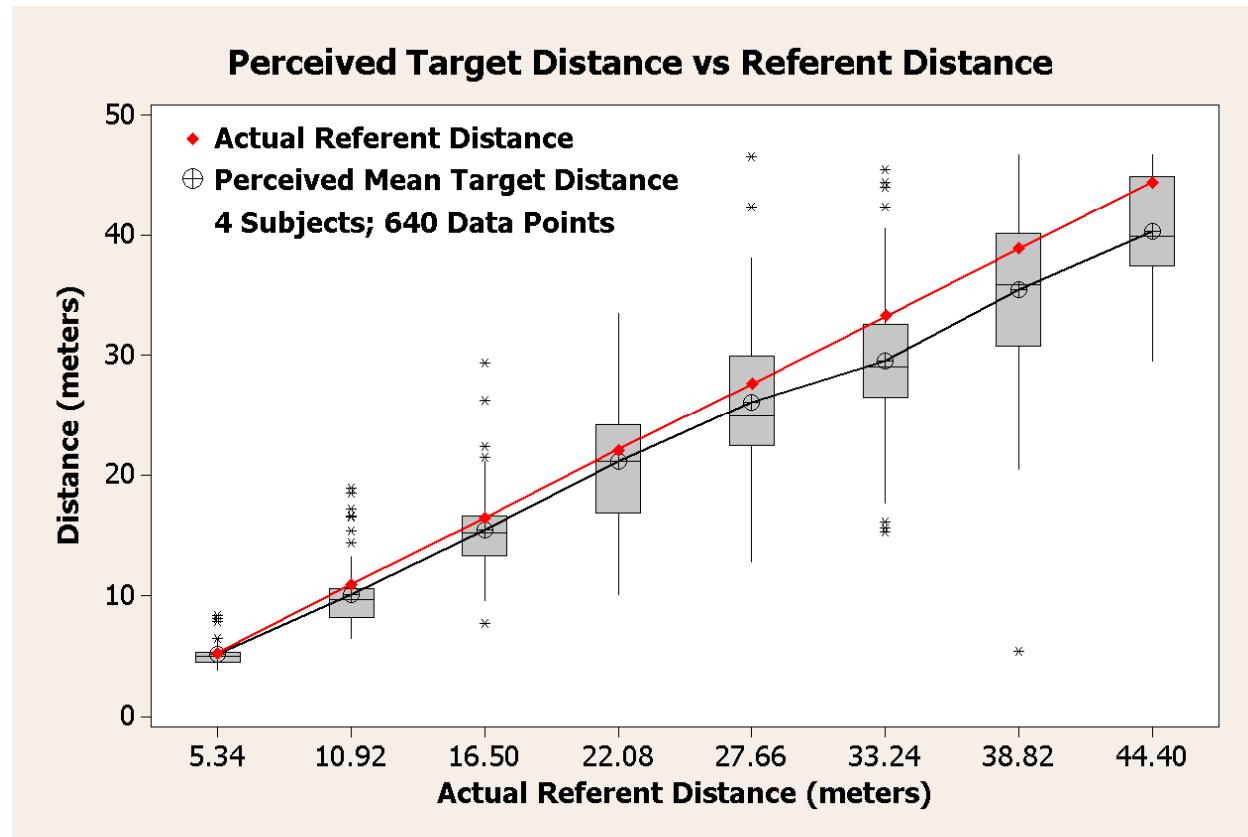
- **EDA** **emphasizes** **median statistics**:
  - median
  - upper hinge, lower hinge
  - upper extreme, lower extreme

- **5 values often drawn as a boxplot:**

- **Calculation of hinges and extremes depends on software**

- **Median statistics insensitive to**
  - Data distribution
  - Outliers

- **Use mean statistics once distribution is established and outliers removed**

outliers

upper
extreme

upper
hinge

median

lower
hinge

lower
extreme

Example Histogram and Boxplot from Real Data

Boxplots Displaying Groups

Perceived Target Distance vs Referent Distance
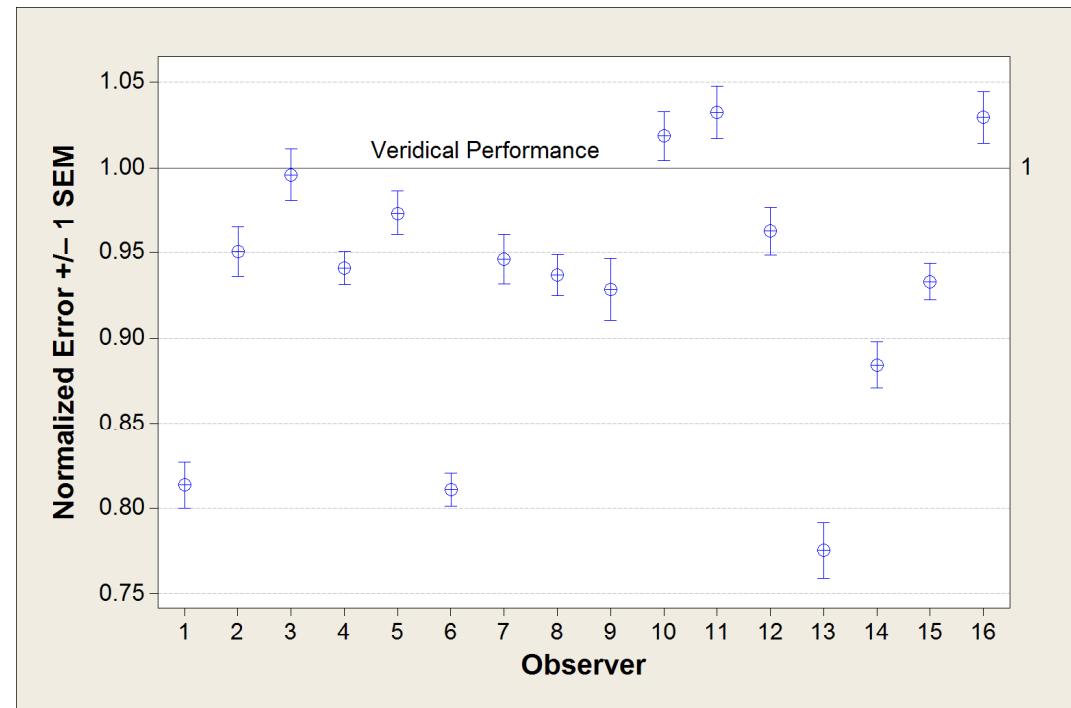
- Emphasizes variation and relationship to mean

- Because narrow, can be used to display side-by-side groups

- EDA includes many other innovative graphical techniques…

Data from [Swan et al 06]
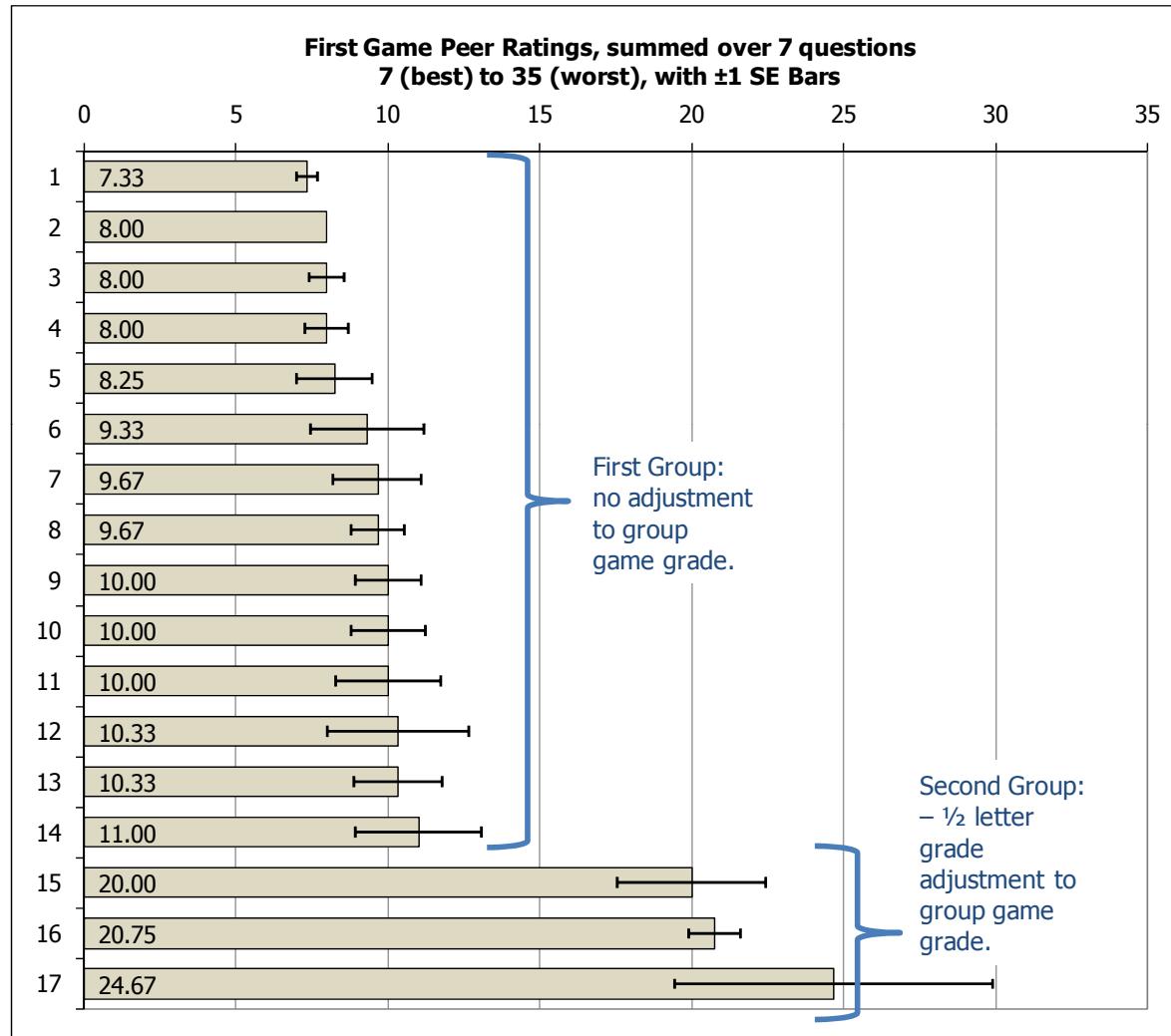
Mean +/– SEM Plots

- **Most important considerations:**
  - **Size of difference between means**
  - **Distance between error bars (separation / overlap)**
    - **Graphical indication of power**
  - **Size of smallest meaningful interval on *y*-axis**

- **Note that considerations are all graphical**
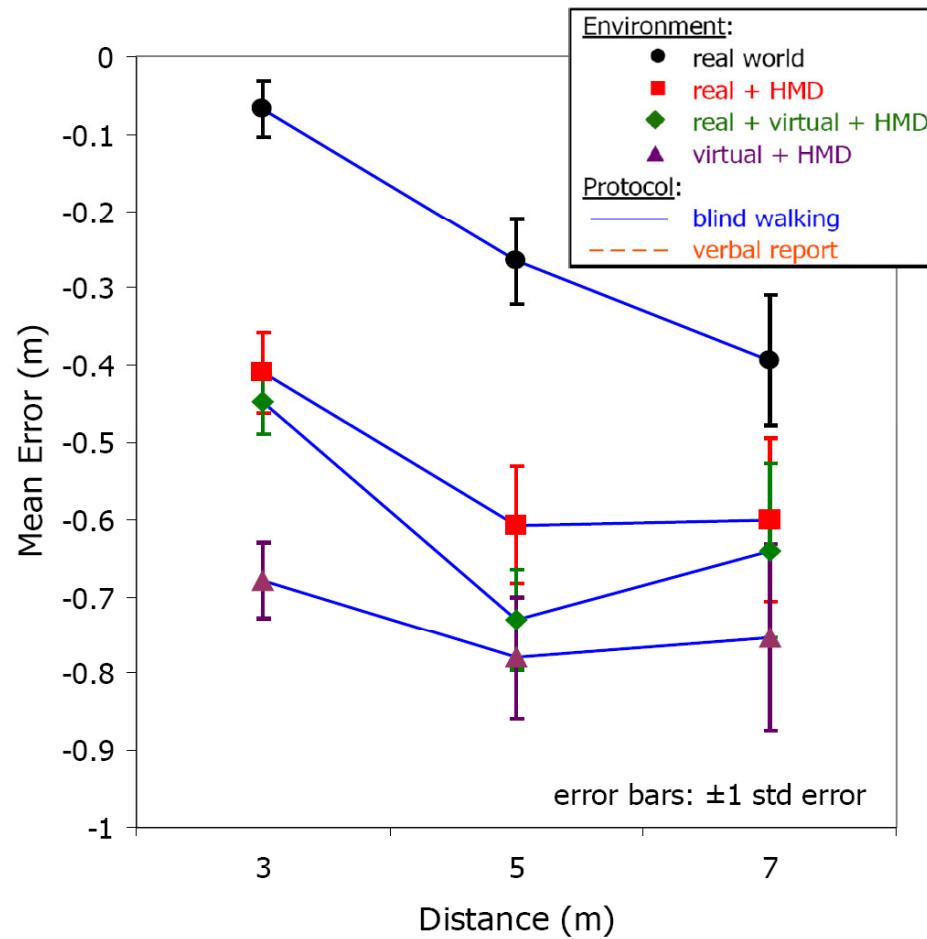
Data from [Jones Swan et al 08]

Mean +/– SEM Bar Graphs

First Game Peer Ratings, summed over 7 questions
7 (best) to 35 (worst), with ±1 SE Bars

First Group: no adjustment to group game grade.

Second Group: – ½ letter grade adjustment to group game grade.

Group	Value
1	7.33
2	8.00
3	8.00
4	8.00
5	8.25
6	9.33
7	9.67
8	9.67
9	10.00
10	10.00
11	10.00
12	10.33
13	10.33
14	11.00
15	20.00
16	20.75
17	24.67

- Error bars give much more context to the results
- Always use error bars if bars showing means

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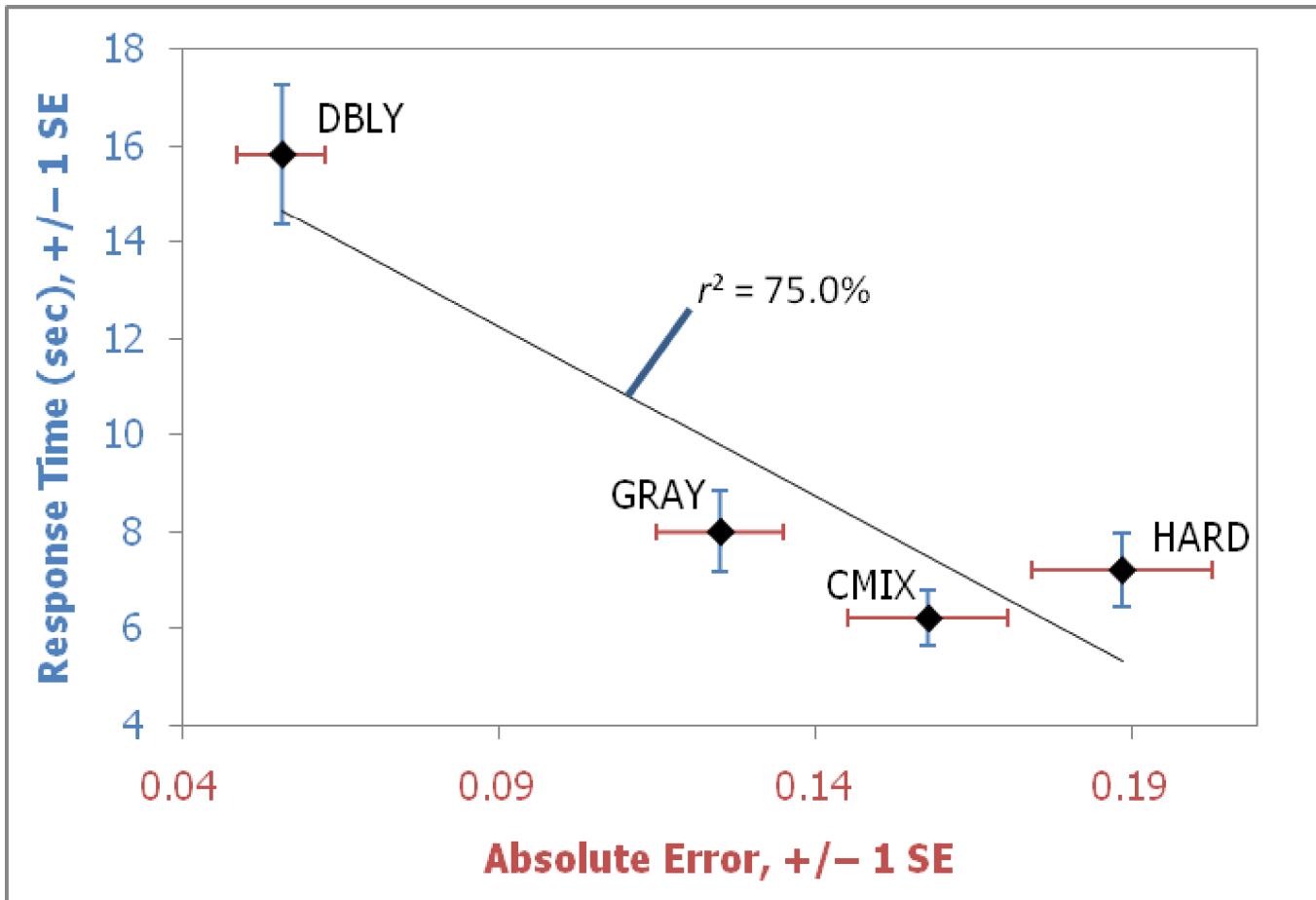
Mean +/– SEM Interaction Plots

- Again, error bars give much more context to the results
- Here, error bars suggest where to group and separate the means
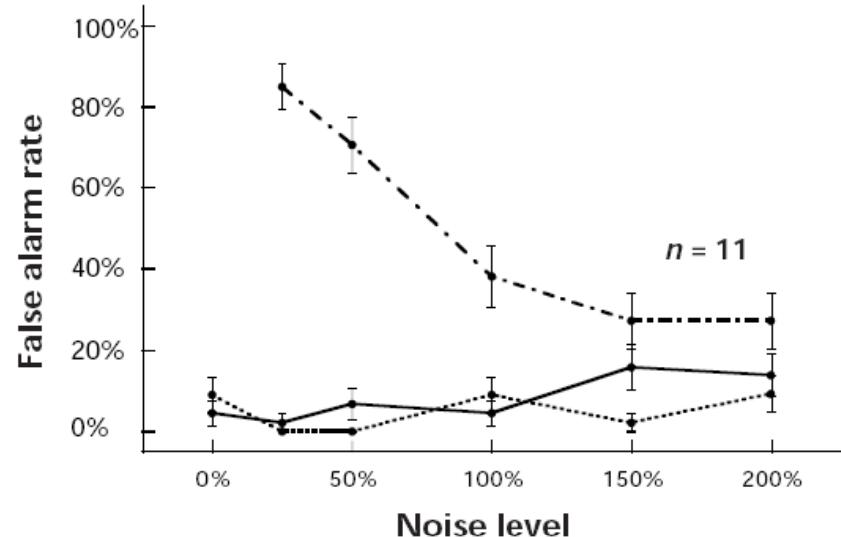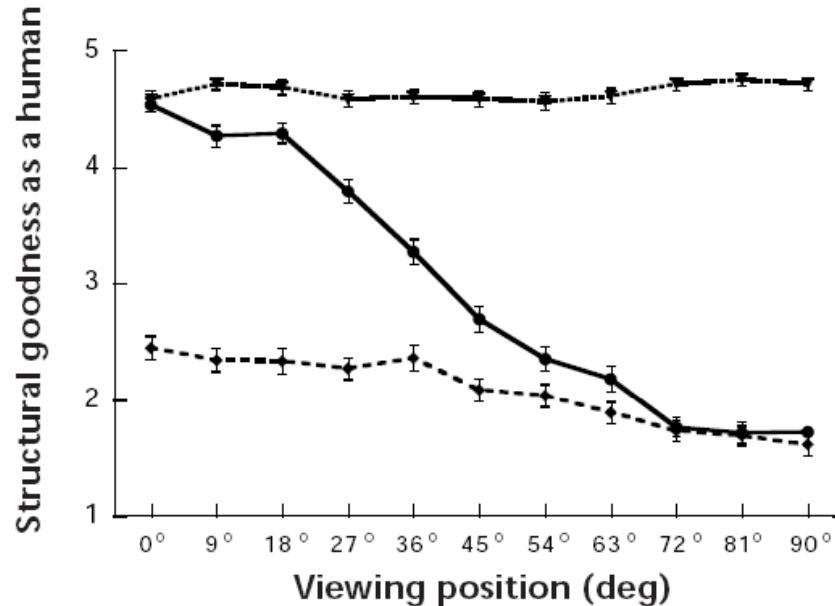
XY Mean +/– SEM Plots

- **Error bars are against both axes**
- **Suggests a clear speed / accuracy tradeoff**

Are Plots All You Need?

- **Two plots from [Bülthoff et al 98],** *Nature Neuroscience*
- **Small error bars relative to**
  (1) effect sizes,
  (2) smallest meaningful interval → large amount of power
- **Paper contains <u>no hypothesis testing</u>!**
- **In some fields (e.g., psychophysics) hypothesis testing culturally unnecessary if plots convincingly show enough power**

My Data Analysis Work Flow

- **Create MS Word data analysis file**
  - Can throw in text and graphics
  - Can organize using headings and outliner

- **In a very non-linear fashion:**
  - Draw histograms and boxplots; understand distributions
  - Remove outliers
  - Draw mean +/– SEM plots
  - Explain dependent measures calculations
  - Hypothesize as to what we (might have) found and why
  - Perform hypothesis testing on interesting results
  - Perhaps collect more data if results look promising but are not yet powerful

- **Eventually determine what is the overall story of the data; what graphs to show**

Example of My Analysis Document

1 Dependent Measures

We have calculated 4 dependent measures:

(1) *judged distance*, (meters)

(2) *error = judged distance – correct distance*, (meters)
error = 0: a veridical answer (no error)
error > 0: increasing overestimation
error < 0: increasing underestimation

(3) *absolute error = | judged distance – correct distance |*, (meters)
absolute error = 0: a veridical answer (no error)
absolute error > 0: increasing overestimation / underestimation; folds the direction of the error together

(4) *normalized error = judged distance / correct distance*, (no units)
normalized error = 1: a veridical answer (no error)
normalized error > 1: increasing overestimation (normalized to units of *correct distance*)
0 < *normalized error* < 1: increasing underestimation (normalized to units of *correct distance*)
Often *normalized error* is considered as a percentage.

2 Ideas
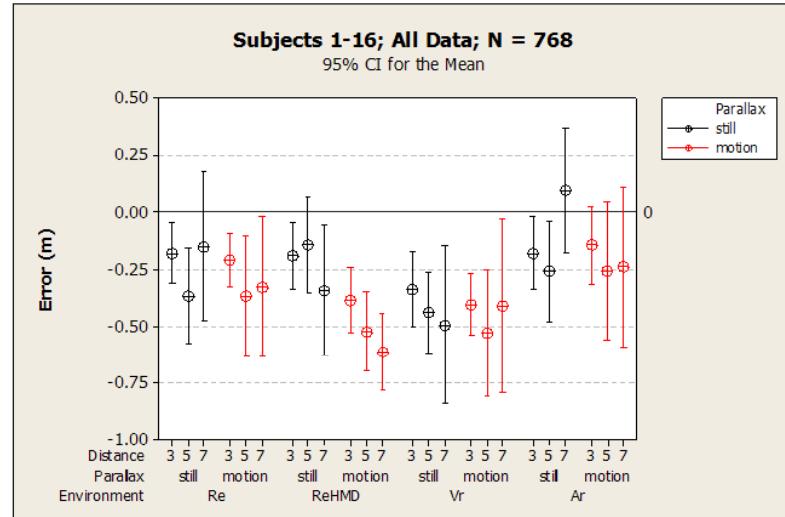
2.1 Analysis Tasks To Do

- Do discriminate analysis to justify splitting out subjects 1, 6, and 13.

- Make and consider "learning" graph.

- Calculate between-results pooled confidence intervals as Laidlaw does. But, we have to us Bonferroni corrections, which reduces power. Howell [1] indicates that Bonferroni corrections loose too much power when there are too many multiple comparisons, and recommends either Ryan REGWQ or Tukey HSD post-hoc tests. Perhaps the better approach is to just use standard error bars, and indicate the a-priori groupings using another method.

- Try removing the .1 meter "correction", just to see what happens.

- Redraw the big graph in Excel 2007.

- Normalize per subject.
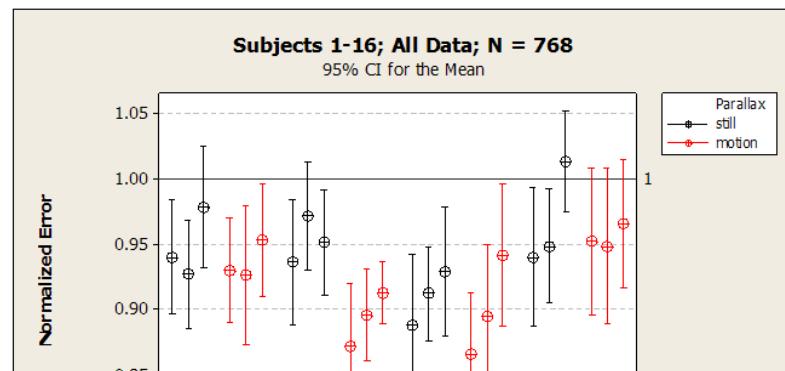
2.2 Overall Findings

- The degree of underestimation for all conditions is low compared to many previous studies.

- There does not appear to be large interactions with increasing distance (the only exceptions: Re / still, ReHMD / still, Ar / still); we could do a power analysis to see how non-existent the distance interaction really is.

4 Analysis (Original Data, with 0.1 meter subtracted)

This graph indicates that the variability of error increases with increasing distance (the confidence intervals tend to increase with increasing distance). This means that the assumption of homogeneity of variance over distance is not met for error, and hence it is not appropriate to perform an ANOVA over distance for error. I believe this also means it is more appropriate to sum over distance for normalized error as well. Run an omnibus ANOVA here.

Final Thoughts on Experimental Design and Data Analysis

- In the end, what matters are:
  (1) the results, and
  (2) how they relate to what's being studied.
- …not hypothesis testing (e.g., [Bülthoff et al 98])

- Paraphrased quote from many applied statistics texts:

  "Data analysis is an art, not a science"

- When applying data analysis to results:
  - There is no one way to be right
  - There is no one way to be wrong

- The best way to learn data analysis and experimental design: read and critique existing papers, both in VR / AR and in other fields.

  "A month in the lab will save you a day in the library"

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[Living Swan et al 03] MA Livingston, JE Swan II, JL Gabbard, TH Höllerer, D Hix, SJ Julier, Y Baillot, D Brown, "*Resolving Multiple Occluded Layers in Augmented Reality*", The 2nd International Symposium on Mixed and Augmented Reality (ISMAR '03), October 7–10, 2003, Tokyo, Japan, pages 56–65.

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[Swan et al 06] JE Swan II, MA Livingston, HS Smallman, D Brown, Y Baillot, JL Gabbard, D Hix, "*A Perceptual Matching Technique for Depth Judgments in Optical, See-Through Augmented Reality*", Technical Papers, IEEE Virtual Reality 2006, March 25–29, 2006.

[Swan et al 03] JE Swan II, JL Gabbard, D Hix, RS Schulman, KP Kim, "*A Comparative Study of User Performance in a Map-Based Virtual Environment*", Technical Papers, IEEE Virtual Reality 2003, March 22–26, Los Angeles, California: IEEE Computer Society, 2003, pages 259–266.

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[Tufte 83] ER Tufte, *The Visual Display of Quantitative Information*, Graphics Press, Cheshire, Connecticut, 1983.

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Slide Location:

http://www.cse.msstate.edu/~swan/teaching/tutorials/Swan-VR2012-Tutorial.pdf

Formative Usability Evaluations

IEEE VR 2012 Tutorial

Joseph L. Gabbard, Ph.D.
**Virginia Bioinformatics Institute / HCI Lab**
Virginia Tech
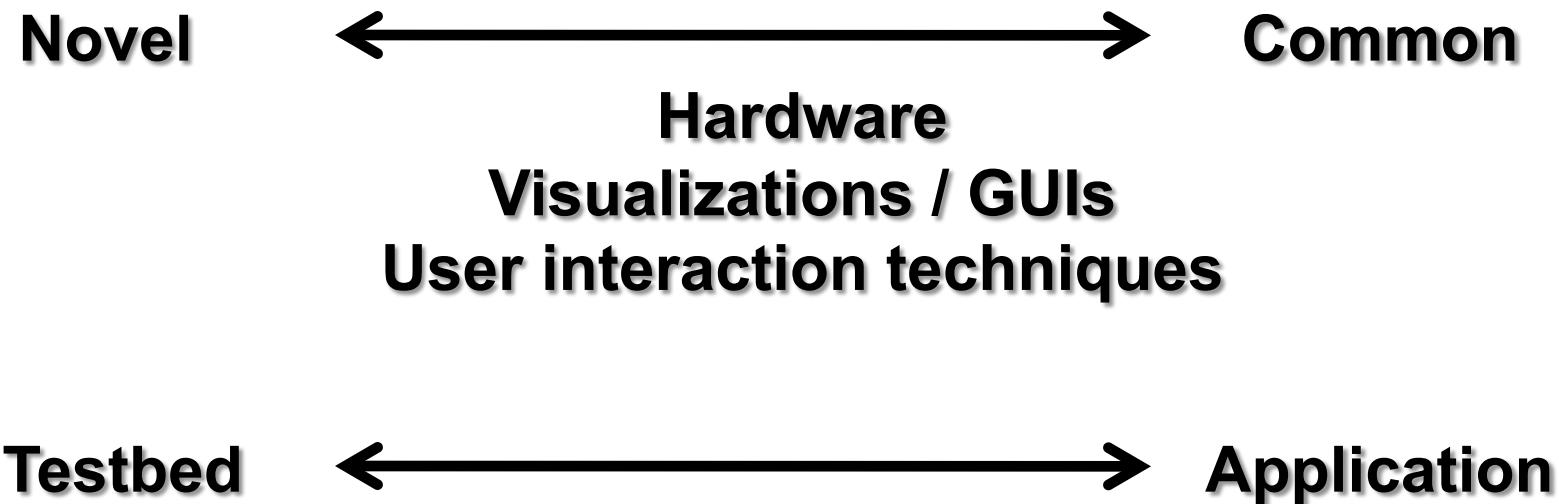
Context

- *Continuum between basic human subject experiments and usability evaluation*

Testbed $\longleftrightarrow$ **Application**

Context

- *Continuum between basic human subject experiments and usability evaluation*

Novel ⟷ **Common**

Hardware
Visualizations / GUIs
User interaction techniques

Testbed ⟷ **Application**

Context

- *Emerging novel technologies* have the potential to change how we use and interact with computers

- As we *advance the state* of these technologies, we also need to…

- *Advance the processes* by which they are designed, built, and evaluated

  "new analyses and metrics" … Ben Shneiderman

- *This session focuses on qualitative processes*

Context - What is Usability?

- **A characteristic of an interactive system that indicates**
  - How easy to use and
  - How useful that system is

- **Usability is related to measurable factors, such as**
  - User task time
  - User errors
  - User satisfaction

  -- User adoption

  -- User retention

- **Usability evaluation (alone) is *not* usability engineering!**

Usability Evaluation

- **Usability evaluations determine usability problems and user performance difficulties**
- **Evaluations are iteratively performed as interface evolves**
- **Expert-based evaluations (usability inspections)**
  - **User interaction and subject matter experts**
- **Formative evaluations**
  - **Representative users performing representative tasks**

Formative Usability Evaluation

- **Formal and informal assessment procedures employed by teachers during the learning process in order to modify teaching and learning activities to improve student attainment [Scriven, 1967]**

- **[Hix & Hartson, 1992] adapted for graphical user interfaces**
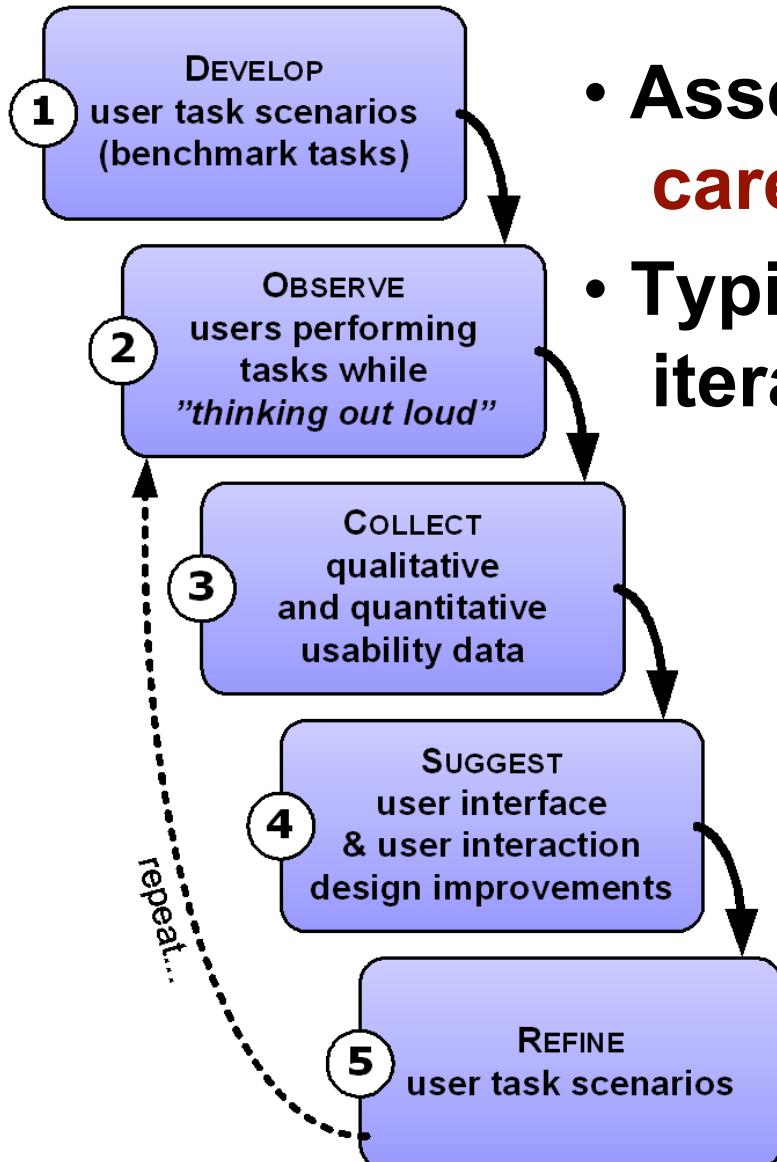
Formative evaluation focuses on usability problems that need to be solved during the prototype design stage before a final design can be accepted for release.

- **Later applied to VR, AR, mobile interfaces, etc.**

Formative Usability Evaluation

- **Evaluation of an interaction design, *as it is being developed***

- Like expert evaluations, goal is to improve the usability of an evolving interaction design

- Should be done early and continually during application development

- Data / results are both qualitative and quantitative

- Can be used to assess user interface designs prior to expensive summative user-based evaluations

Formative Usability Evaluation

- **Assessment with representative, carefully chosen users**

- **Typically need 3 - 4 users per iteration per user class**

  - **Iteratively determine and improve usability**

    – **User follows explicit task scenarios**

    – **User "thinks aloud" while working**

    – **Evaluators produce redesign suggestions based on results**

Formative Usability Evaluation:
Think Aloud Protocol

- **Commonly employed technique in various HCI methods**
- **Users are asked *speak their thoughts* as they perform a task**
- **Useful in *understanding mistakes* that are made**
- **What the causes might be**

Gaining INSIGHT on WHY a usability problem occurred

- **How the interface could be improved to avoid those problems**

Formative Usability Evaluation:
Planning - Developing User Tasks

- **Tasks based on**
  - For applied research: Results of domain analysis or
  - For basic research: Simple, atomic tasks that require little to no domain-specific cognition
- **Structured use:** Identification of *representative, frequent,* and *critical* tasks
  - **Benchmark tasks**
    - Usually take metrics during performance (e.g., task time)
  - **Informal tasks**
    - Other tasks a user may perform; no metrics taken
- **Exploratory use:** No specific tasks given to user
  - "Free play" for user

Formative Usability Evaluation:
Planning –What are Good User Tasks?

- **Achievable** from current screen/state
  - The overall tasking can cover many screens/states
- **Completed by a single path**
  - If you want to compare tasks times across users
  - Good for feedback on particular UI element
  - Multiple paths can be appropriate for certain studies
- **Have a clear end state**
  - Helps w/ quantitative measures
- **May require users to explore**
  - For example, may have to click on a visible object to get more information (in order to complete task)
  - Does the UI afford an action?

Formative Usability Evaluation:
Planning - Representative Users

- ## How many users is enough?
  - **80% of usability problems are detected with 4 to 5 users**
  - Most severe usability problems are typically detected by first few users
  - Could need many more users
    - Sometimes find numerous new problems with 10th or 20th user
    - Especially true for complex applications (such as VRs / ARs) with large scope; different users evaluate different parts

More details in: *R.A. Virzi. (1992). Refining the test phase of usability evaluation: How many subjects is enough? Human Factors, 34(4).*

Formative Usability Evaluation:
Planning - Assigning Team Roles

- **Formative evaluation session roles include:**
  - **Evaluator:** Directs evaluation session; develops rapport with users; keeps session moving
  - **Observer(s):** May help collect data (especially qualitative); SWDs can help here!
  - **Subject matter expert (SME):** Helpful when evaluating complex domain-specific application(s)
  - **Technician:** To assure smooth operation of hardware and software
  - **Consultant / Experienced evaluator:** Helpful for first few times planning / performing / analyzing formative evaluation sessions

Formative Usability Evaluation:
Collecting Data

- **Evaluators collect both quantitative and qualitative data**

- **Quantitative: Task times, user errors, etc.**
  - Used for simple / course / descriptive stats
- **Qualitative: Critical incidents, comments, concerns**

Formative Usability Evaluation:
Critical Incidents

- Something that happens while user is working that has a *significant effect* on task performance or user satisfaction
- *Indicators of usability problems*
- Generated by participant behavior; evaluator must *recognize and capture* incidents
- Captured in *real-time* occurring as the behavior unfolds

Formative Usability Evaluation:
Critical Incidents
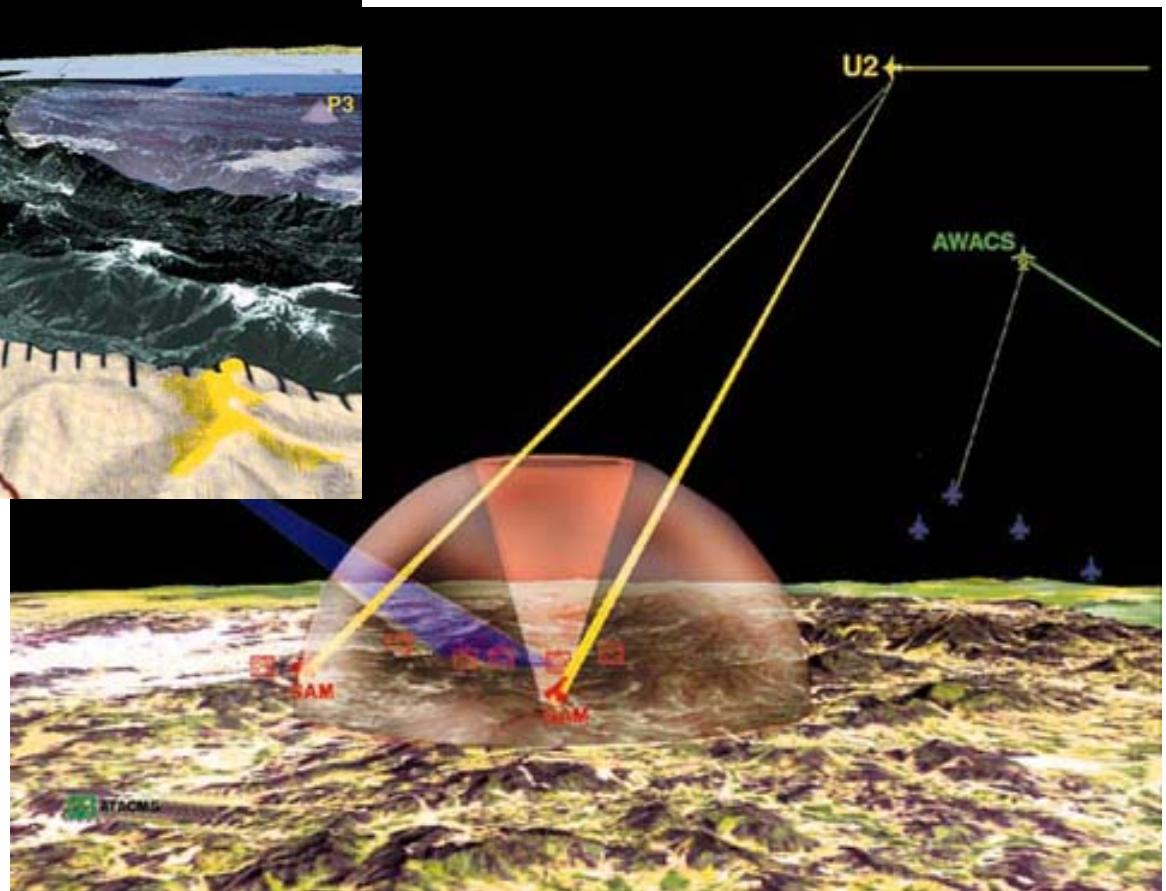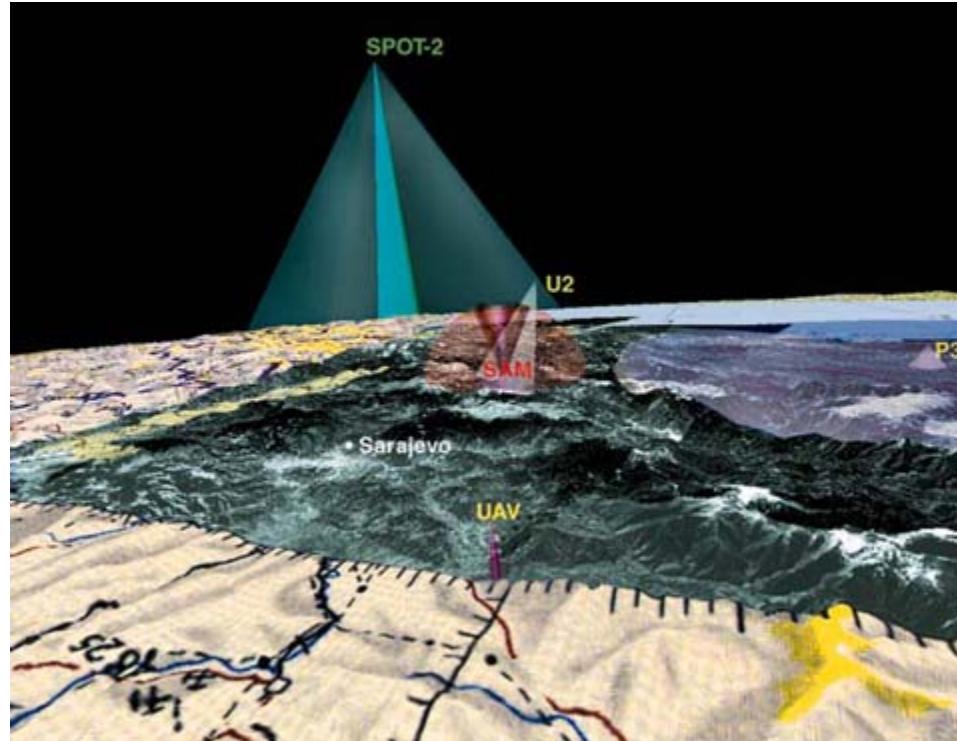
- **Interpretation is often straightforward**
  - principal cause of the can be attributed in the local context of user interaction (e.g., the name of a menu item may have suggested an operation that was not intended)

- **Engaging users** at this time is paramount
  - What were you tying to do?
  - What did you expect to happen?
  - What do you think you should try now?

- Arguably the *most important data* collected during formative evaluations

Be wary of single occurrences!

Formative Usability Evaluation:
Example Data Collection Form

1. Identify the highway number of the long road running east-west in the upper northeast area of the map?	(24)		
2. Identify the name of the swamp that is in the middle of the western edge of the map.	(Great Sandy Run Swamp)		
3. There is a river that divides the map into two halves, called the New River. Find the bay that is part of the New River called Stone Bay.			
4. Read aloud the names of three creeks that flow into Stone Bay.	(Everett, Stone, Millstone, Muddy, Mill)		
5. Find a town called Peru next to the New River.			
6. Position the map so that Peru is	Centering:		

Formative Evaluation Example:
Dominant Battlespace Command (DBC)

Formative Evaluation Example:
Dominant Battlespace Command (DBC)

Visual Representation of 3D Information in Virtual Environments

Formative Evaluation Example:
## Dominant Battlespace Command (DBC)

- **Some exemplar results from DBC formative evaluation**
  - Better visualizations of sensor domes
  - Need mechanisms to control visual clutter and manage drill down
  - Better label placement algorithms
  - Workbench users need basic user interaction (or the 3DUI wasn't done right!)

Formative Usability Evaluation:
Analyzing Results

- **Simple statistical measures** (e.g., mean, median, etc.) used to examine quantitative data
  - Identify tasks or task sequences that systematically require more time or induce more error
  - Review notes or video to figure out WHY
- **Qualitative results and critical incident notes indicate best opportunities for improvements to usability, including:**
  - Missing functionality or information needed to complete task
  - Confusing or inconsistent language
  - Overwhelming number of steps or UI components needed to complete a single task
  - Also software errors or system crashes

Formative Usability Evaluation:
Analyzing Results

- **Wealth of (re)design suggestions ranging from minor & mundane to significant**

- **Generally too many problems to address at once**

- **Requirements are condensed, organized and grouped**

- *Cost-benefit analyses* **to prioritize requirements**
  - **Determine scope and priority for releases**
 - **Mitigate tendency to "design by panic"**
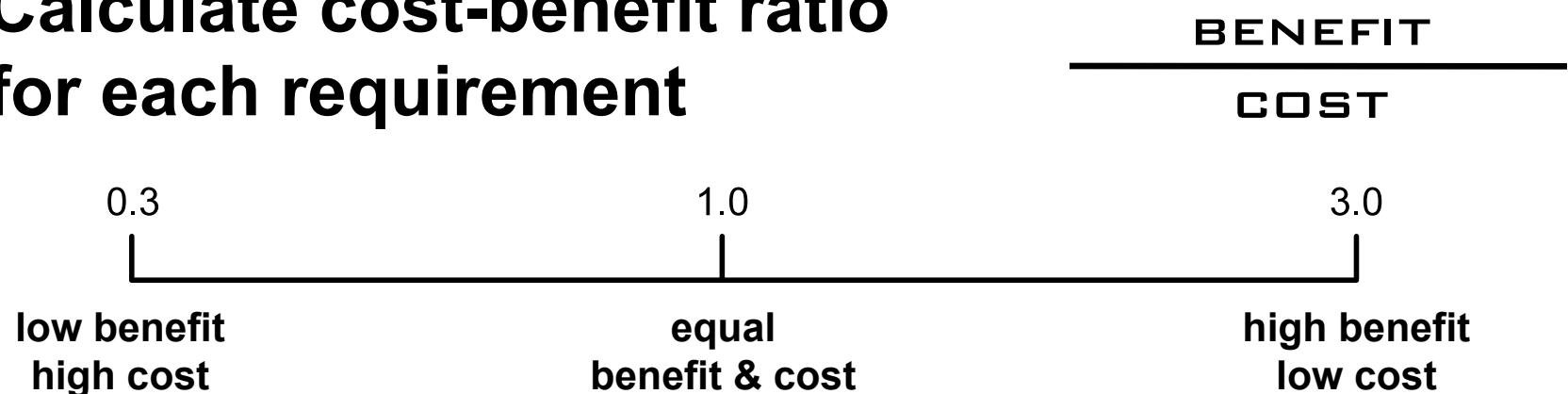
Formative Usability Evaluation:
Analyzing Results

- *Independently score* all requirements
  - By cost: software developers
 - By benefit: stakeholder, representative users, management
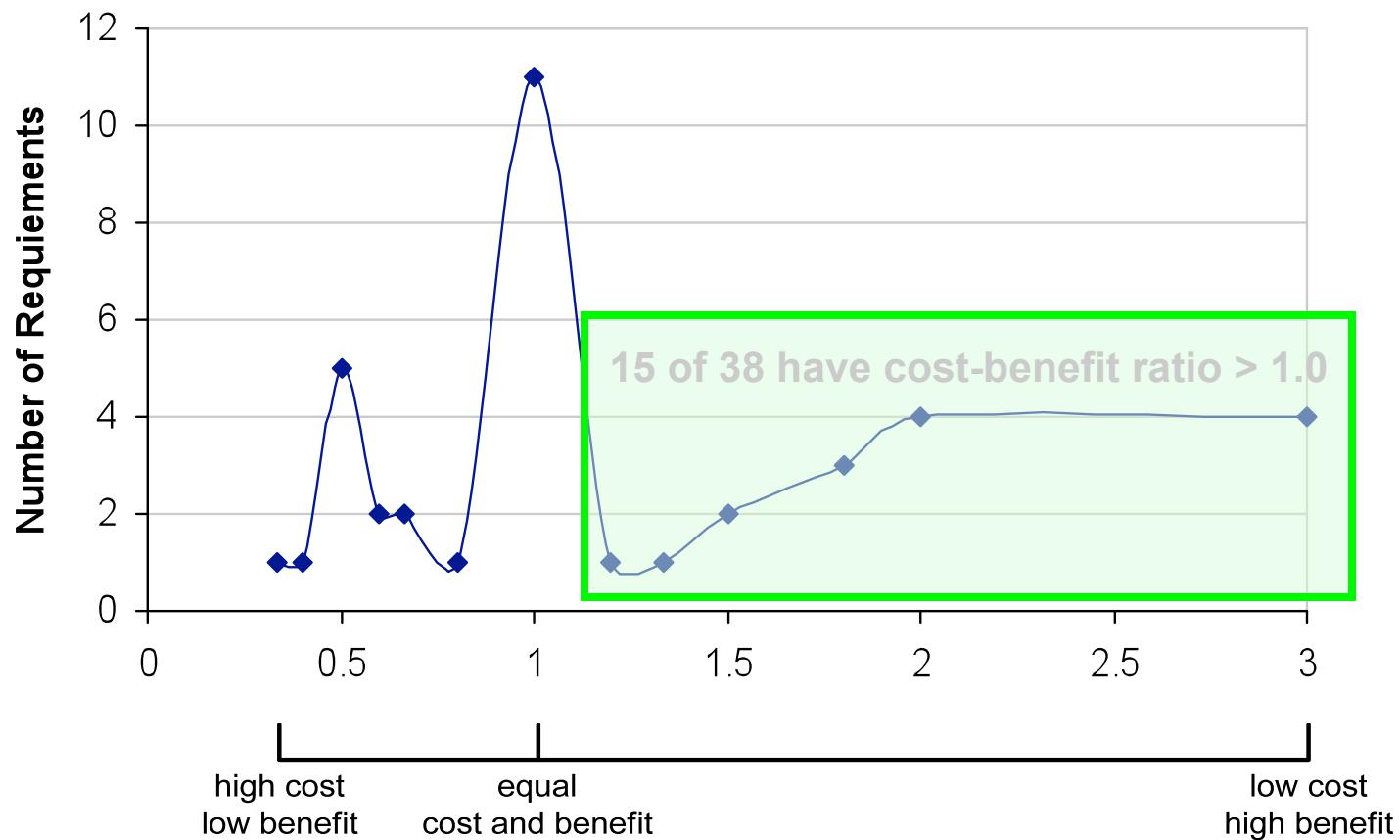
Cost	Benefit
1 = High Cost	1 = High Benefit or Importance
2 = Medium Cost	2 = Medium Benefit or Importance
3 = Low Cost	3 = Low Benefit or Importance

- **Calculate cost-benefit ratio for each requirement**

$$\frac{\text{BENEFIT}}{\text{COST}}$$

0.3	1.0	3.0
low benefit high cost	equal benefit & cost	high benefit low cost

Formative Usability Evaluation:
Analyzing Results

Sample Distribution of 38 Requirements

15 of 38 have cost-benefit ratio > 1.0

Number of Requiements

high cost
low benefit

equal
cost and benefit

low cost
high benefit

Formative Usability Evaluation:
Analyzing Results
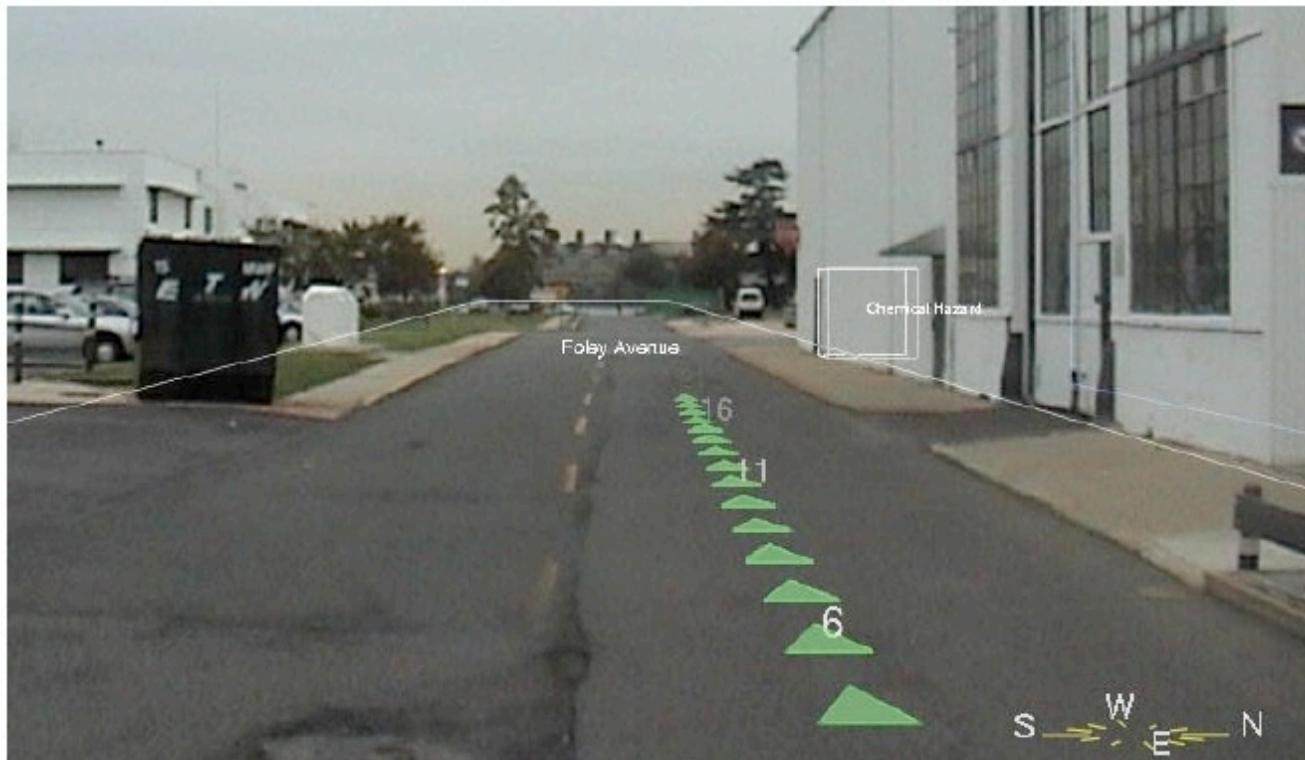
- **Prioritize results for development team based on**
  - **Cost/Benefit Ratio: Balances the cost of fixing the issues with benefit to users**
  - **Probability of occurrence: Over all affected user classes, how often will users encounter this problem?**
  - **Learnability: If users learn to work around problem immediately, likely won't affect subsequent usage**

Formative Usability Evaluation:
Iterating Based on Results

- **Developers implement chosen design solutions**
- **If time and schedule permit, iterate back through usability engineering life cycle process and evaluate again**

- **Goal is not perfection**

Formative Usability Evaluation Example:
BARS

- *Augmented Reality* is a display paradigm that mixes computer-generated graphics with a user's view of the real world

Formative Usability Evaluation Example:
BARS

- **Evaluation goal:** To empirically address issues that most directly improve user task performance in an urban warfighting domain
  - Specifically, continue with empirical determination of how best to convey occluded information to users
  - Scientific approach, in a controlled, but application-context, environment
- *Challenge*: Working in outdoor, mobile, highly dynamic environment while wearing BARS
- Was performed on the heels of expert evaluation

Formative Usability Evaluation Example:
BARS

- **Involved representative users (Marines) in several aspects of occlusion, similar to those from expert evaluations, including:**
  - **How to graphically represent occluded domain information / objects (e.g., buildings, personnel, military assets)**
  - **How to present textual information**
  - **How to minimize clutter of augmented information**
  - **How to distinguish between static and dynamic objects**
  - **How to support user control of augmented information**

Formative Usability Evaluation Example:
BARS

- **Five users**
  - 3 Marines
  - 2 user interface / AR experts

Formative Usability Evaluation Example:
BARS
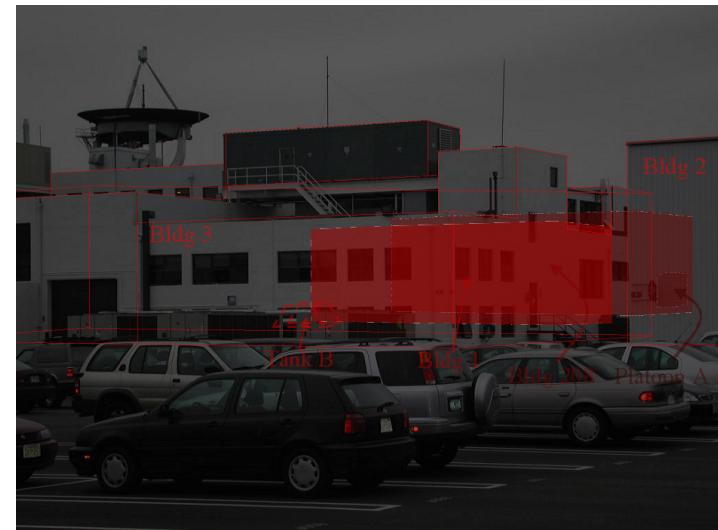
- ## Equipment
  - BARS computer on portable cart
  - Precise outdoor tracking, using specially-designed tracking cage

Formative Usability Evaluation Example:
BARS

- ## User tasks

  - **Militarily relevant tasks, inspired by Naval / Marine scenarios to attack and neutralize a specific military objective**

  - **Finding specific information from augmented graphics and text**

  - **Simple examples:**

    - **Which enemy platoon is nearest you?**

    - **Where are restricted fire areas? Where are other friendly forces?**

    - **Estimate the distance between the enemy squad and yourself.**

    - **What direction is the enemy tank traveling?**

Formative Usability Evaluation Example:
BARS

- **Users performed approximately 85% of tasks correctly and efficiently with less than 10 minutes of training using BARS**
  - Strong result of iterative, expert evaluation
- **Users had very positive, enthusiastic reaction to BARS and its capabilities**
  - Would use BARS as a "reference tool", taking it off and on as needed in the field
  - Wanted one-handed interaction

Formative Usability Evaluation Example:
BARS

- **Qualitative results**
  - Objects must be perceived as 3D (shading of objects worked better than wireframe for this)
  - Smooth integration of "in-the-scene view" (real world) and "god's-eye view" (map) important
  - No more than 3 - 4 levels of occlusion
  - Users must be able to easily control depth / distance information
  - Textual information must be clearly associated with object it is augmenting (e.g., building label)

Formative Usability Evaluation Example:
BARS

- ## Comments from Marines

  "I thought this would be useful only for the forward observer. But having tried it, I see it would be useful for any unit."

  "This would be a great, great piece of gear."

 "I would use it in a MOUT exercise if given the opportunity."
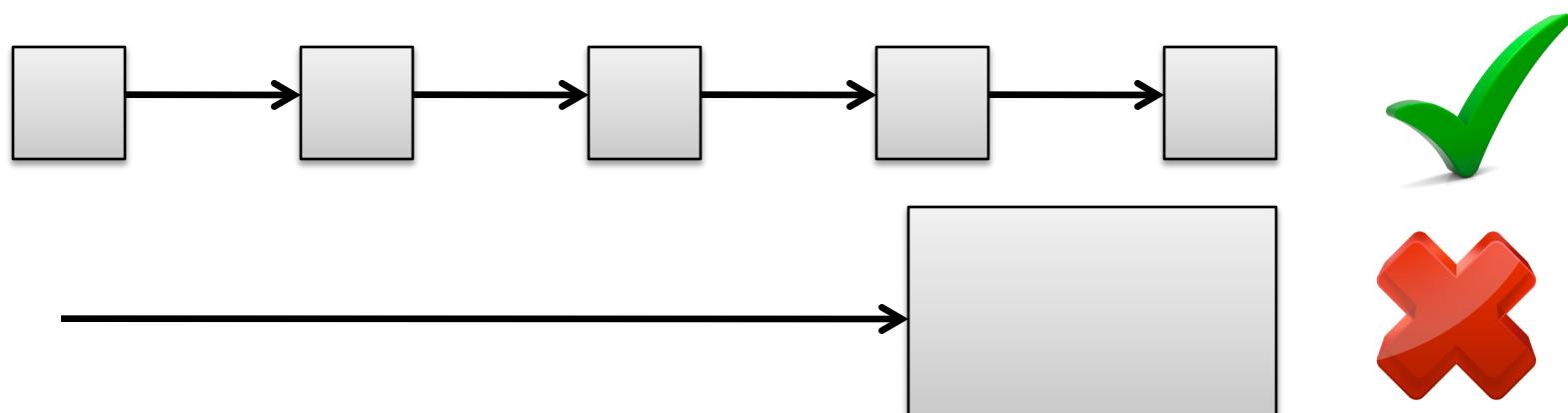
  "It has to be easy to use."

  "When establishing situational awareness, it's easy to remember a picture."

Lessons Learned
Conducting Formative Evaluations

- **Pay careful attention to *representative user tasks***

- **Strive for ecological validity**

- **Keep evaluations *small* and *focused***

- **Use results and finding from each study to inform subsequent studies and to *foster insight and innovation***
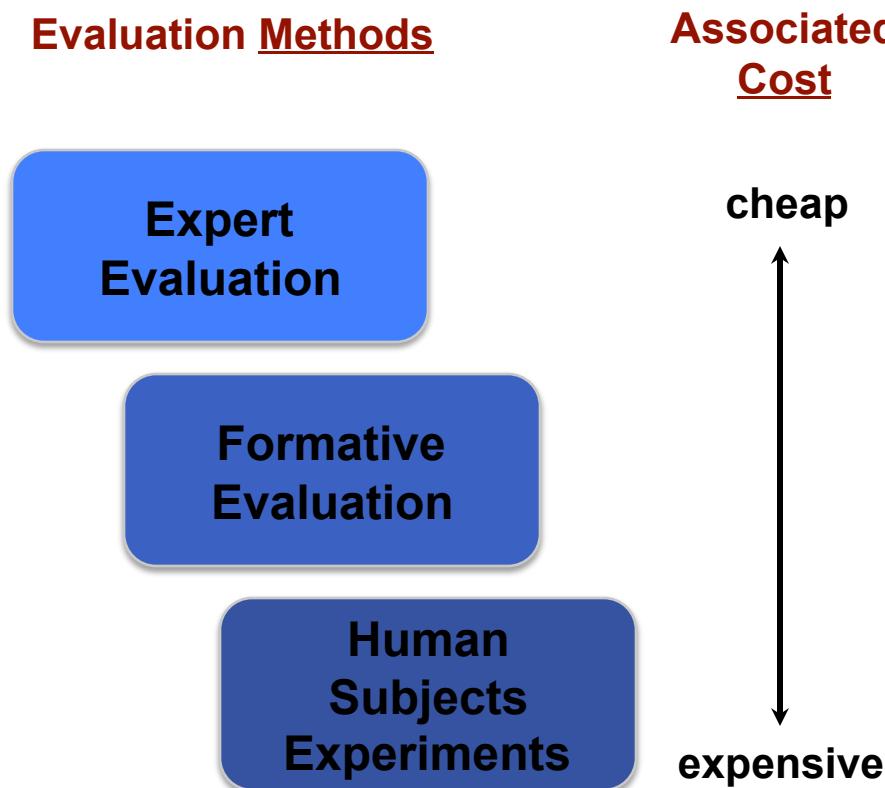
Comparisons & Connections

Connections

- **Many years of HCI work with**
  - Human-subject experiments
  - Expert evaluations
  - Formative evaluations
- **In HCI, "it depends" is a common answer**
- ***Comparisons* across methods**
- **Interesting scenarios where these these *methods can intersect***
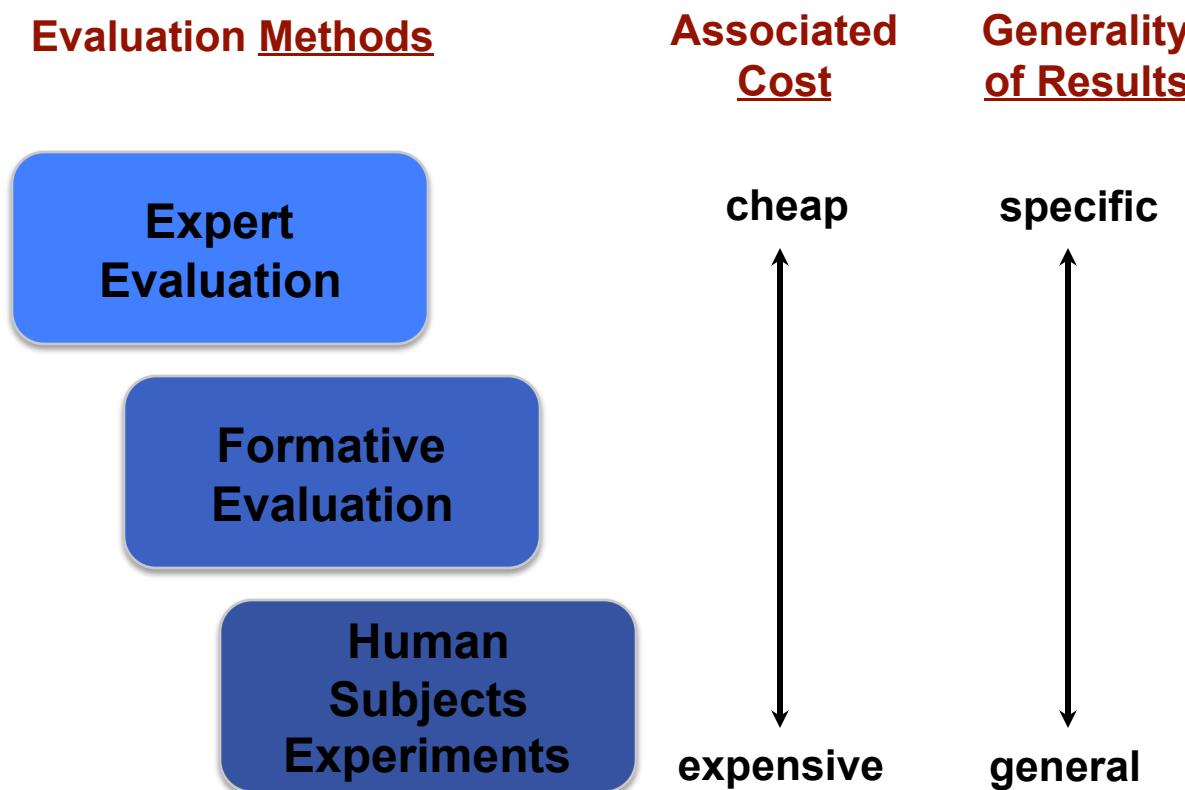
Comparing Evaluation Methods
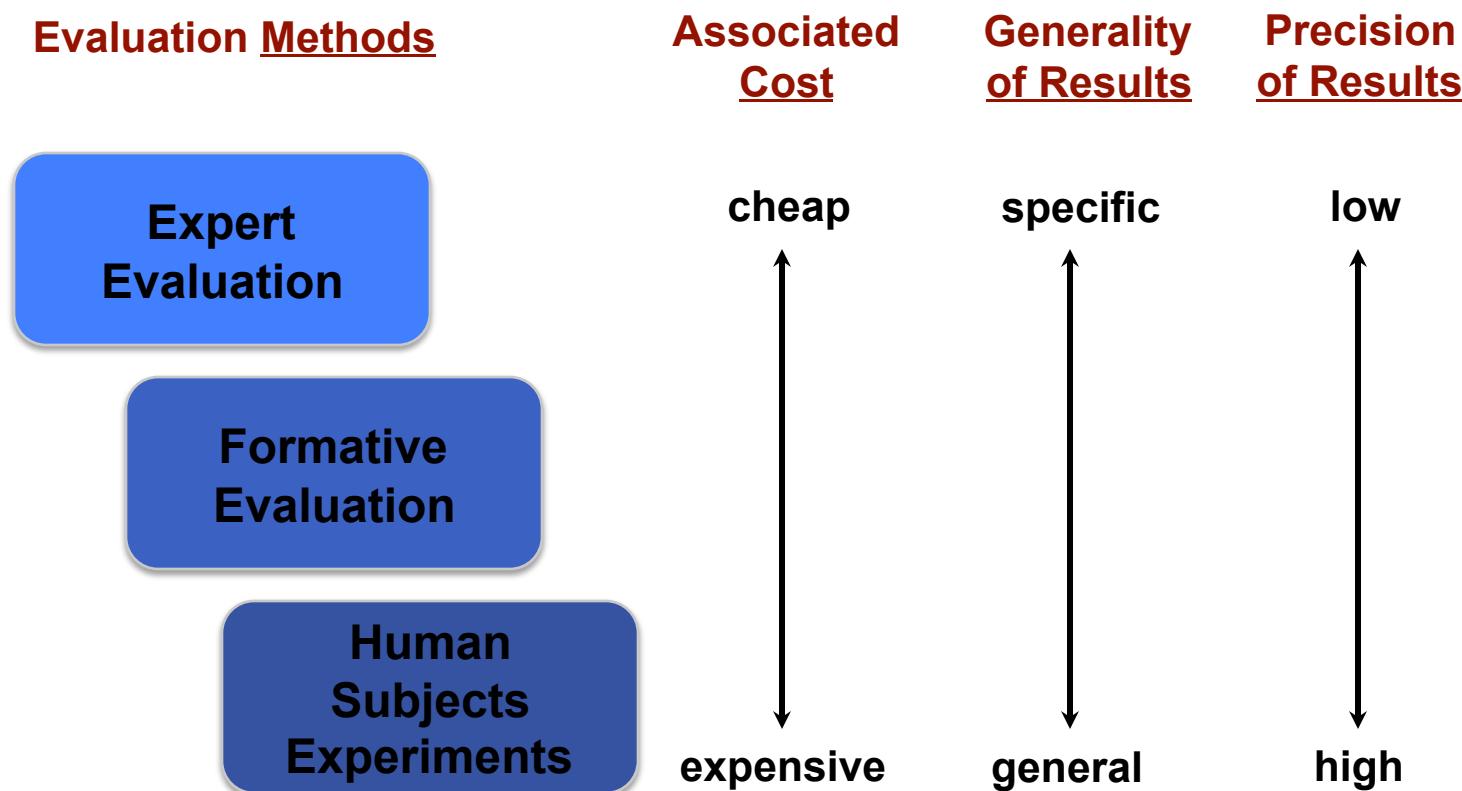
- *Cost* varies based on type of evaluation

Evaluation Methods

Associated Cost

Expert Evaluation

Formative Evaluation

Human Subjects Experiments

cheap

expensive

Comparing Evaluation Methods

- *Cost* varies based on type of evaluation

Evaluation <u>Methods</u>	Associated <u>Cost</u>	Generality <u>of Results</u>
Expert Evaluation	cheap	specific
Formative Evaluation		
Human Subjects Experiments	expensive	general

Comparing Evaluation Methods

- *Cost* varies based on type of evaluation

| Evaluation Methods	Associated Cost	Generality of Results	Precision of Results
Expert Evaluation	cheap	specific	low
Formative Evaluation	↕	↕	↕
Human Subjects Experiments	expensive	general	high
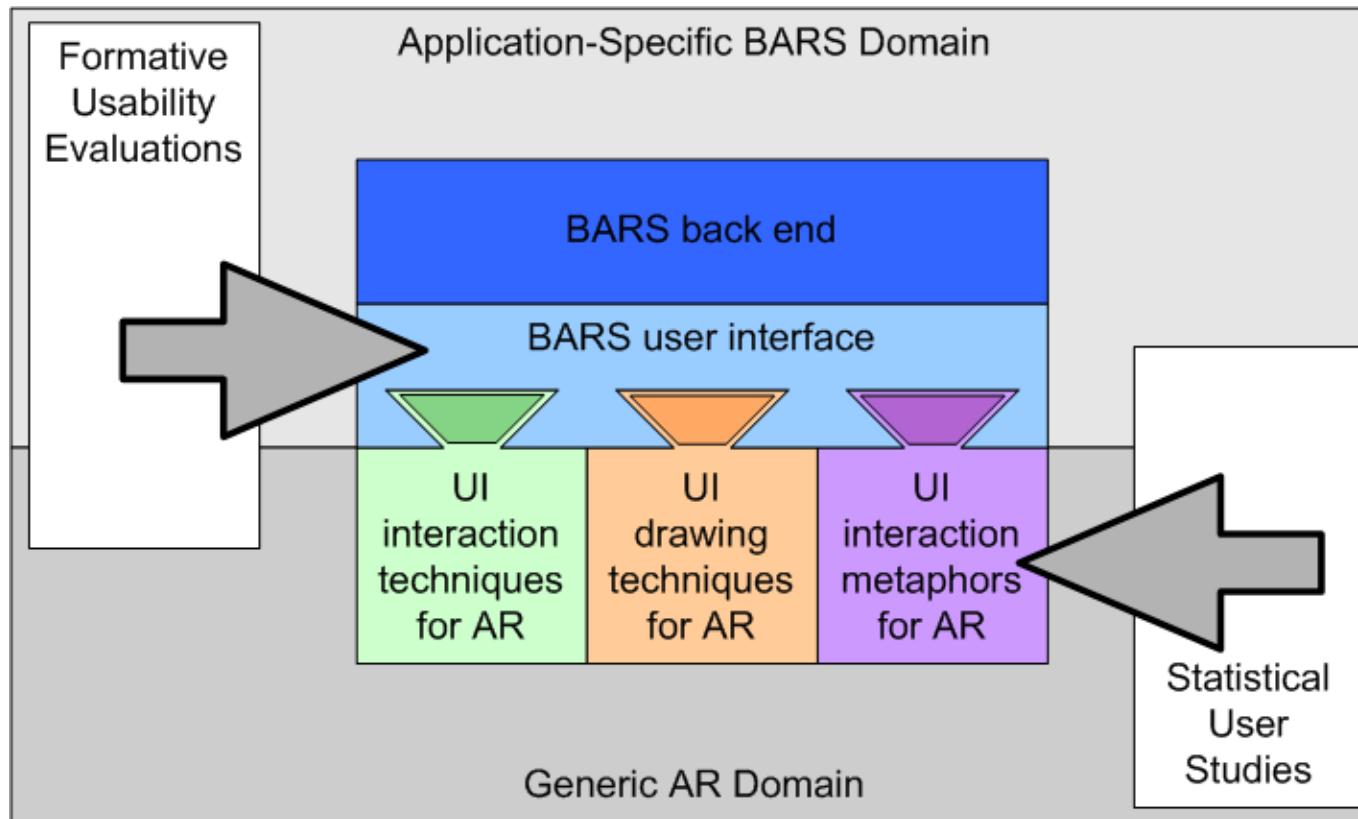
Formative Evaluations & Human-Subject Experiments

- *Human-Subject Experiments* can assess the effectiveness of designs for novel emerging user interface components
  - Lack of standards, metaphors, and design guidelines
    - Not guaranteed a keyboard and mouse
    - Windowing metaphor not necessarily effective
  - User tasks are *not necessarily* domain-specific; may be designed to assess human perception and performance
- *Results* can be used as basis for creating UI prototype design
- *Expert and formative evaluations* can then be applied to UI prototype design
  - Iteratively assess how UI design(s) support domain-specific tasks

Formative Evaluations & Human-Subject Experiments

- **One approach: alternating cycles of**
  - **Formative: improve specific product**
  - **HS Experiments: contribute to body of knowledge**

Formative Evaluations & Human-Subject Experiments

AR Example
Human-subjects Experiments & Formative Evals

AR Example
Human-subjects Experiments & Formative Evals

- Conducted several expert and formative evals
- Produced scores of findings and potential *design recommendations* for the BARS prototype

- Led to *critical juncture* in applying traditional UE techniques to BARS
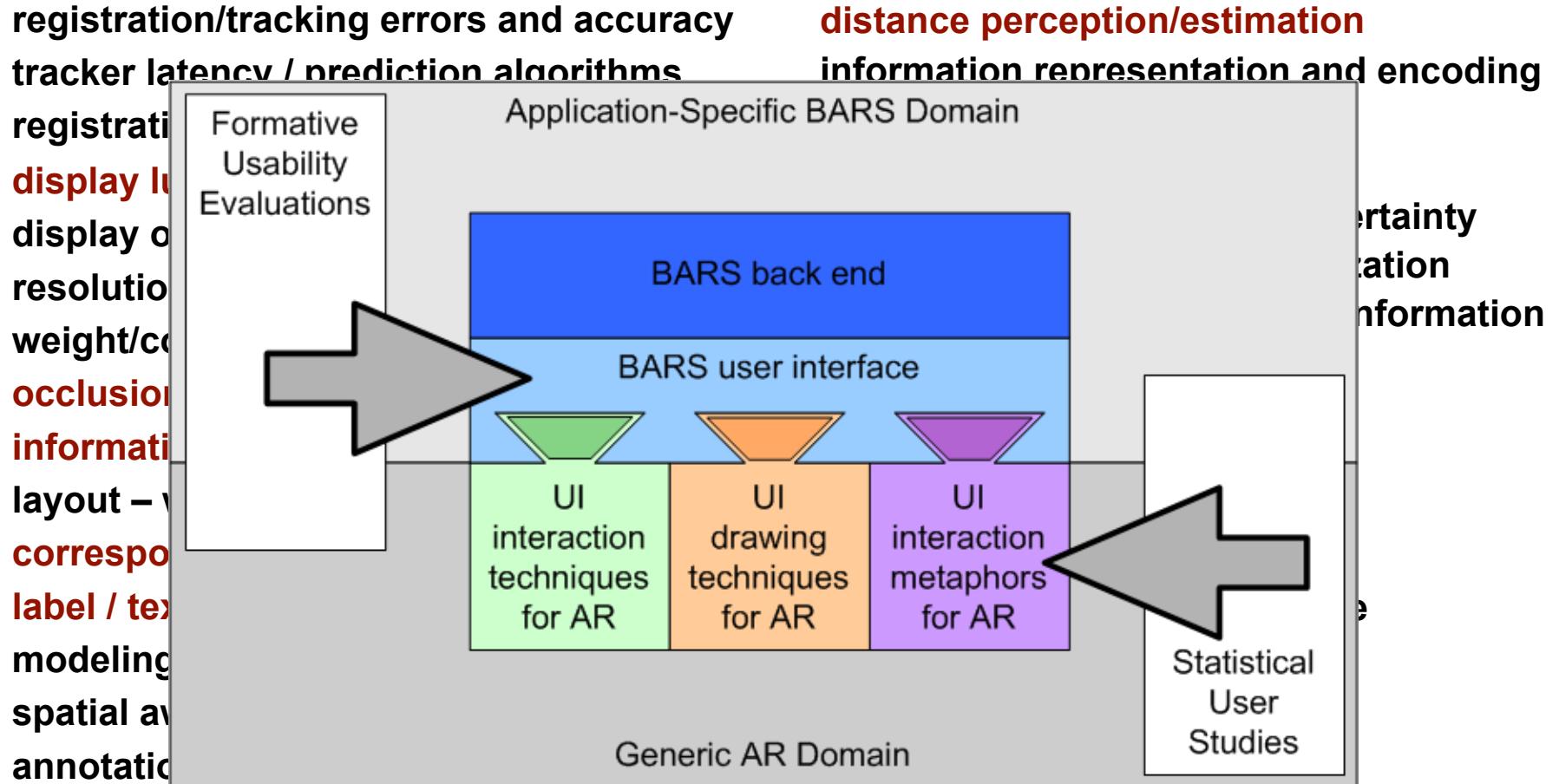
AR Example
Human-subjects Experiments & Formative Evals

- **Two major questions at product & process level**
  - *How to effectively design and develop a quality BARS UI?*
  - *How to modify/extend our existing usability engineering plan to address difficult AR design activities?*
- **Identified 25 *core scientific issues***

AR Example
Human-subjects Experiments & Formative Evals

registration/tracking errors and accuracy

tracker latency / prediction algorithms

registrati...

display lu...

display o...

resolutio...

weight/c...

occlusion...

informati...

layout – ...

correspo...

label / tex...

modeling...

spatial av...

annotatio...

distance perception/estimation

information representation and encoding

...rtainty

...tation

...nformation

Formative Usability Evaluations

Application-Specific BARS Domain

BARS back end

BARS user interface

UI interaction techniques for AR

UI drawing techniques for AR

UI interaction metaphors for AR

Statistical User Studies

Generic AR Domain

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