Traditional vs. Simulation-Based:
Curricula Comparison in a Small Scale Educational Experiment

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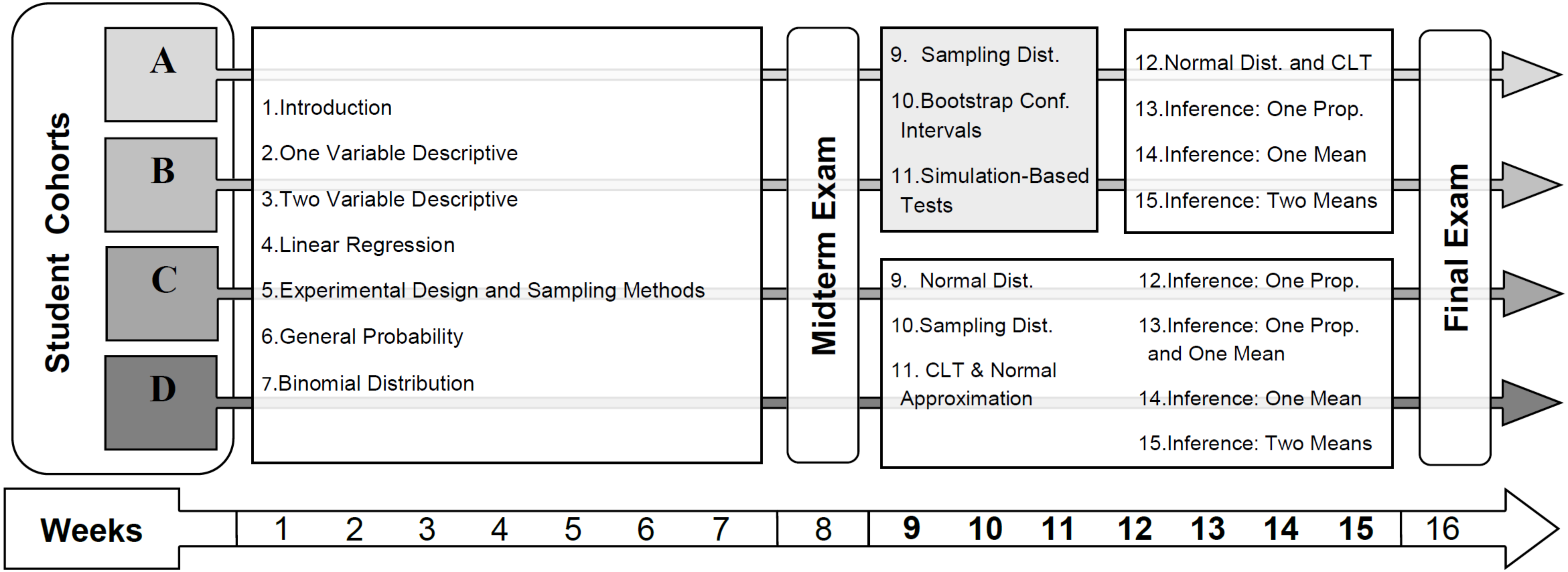
Study Overview

Goal: Compare student learning outcomes under traditional and simulation-based introductory statistics curricula

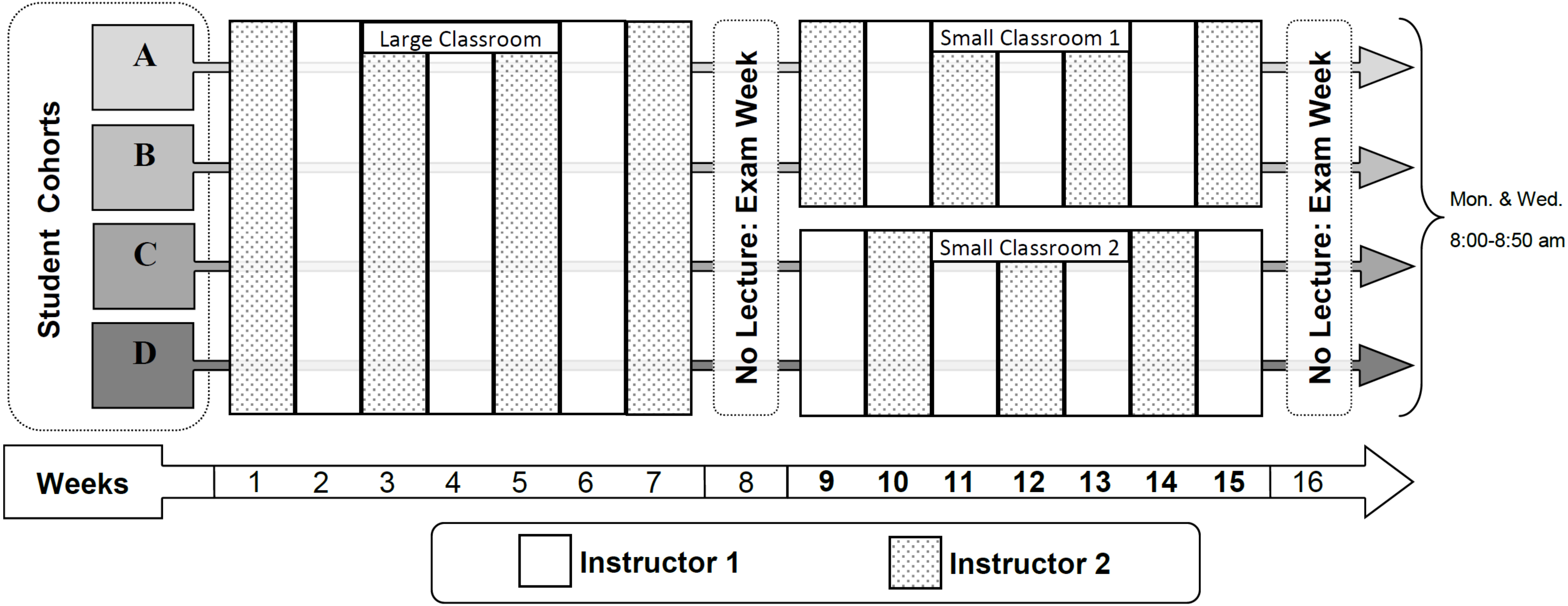
Experimental Design:

- 112 Intro Stat students randomly assigned to the two inference curricula
  - 11 Students did not consent to data release
  - 101 Students consented to data release
- Utilized co-teaching structure and room scheduling achieve this design
- Model-based approach to assess learning outcomes on final exam

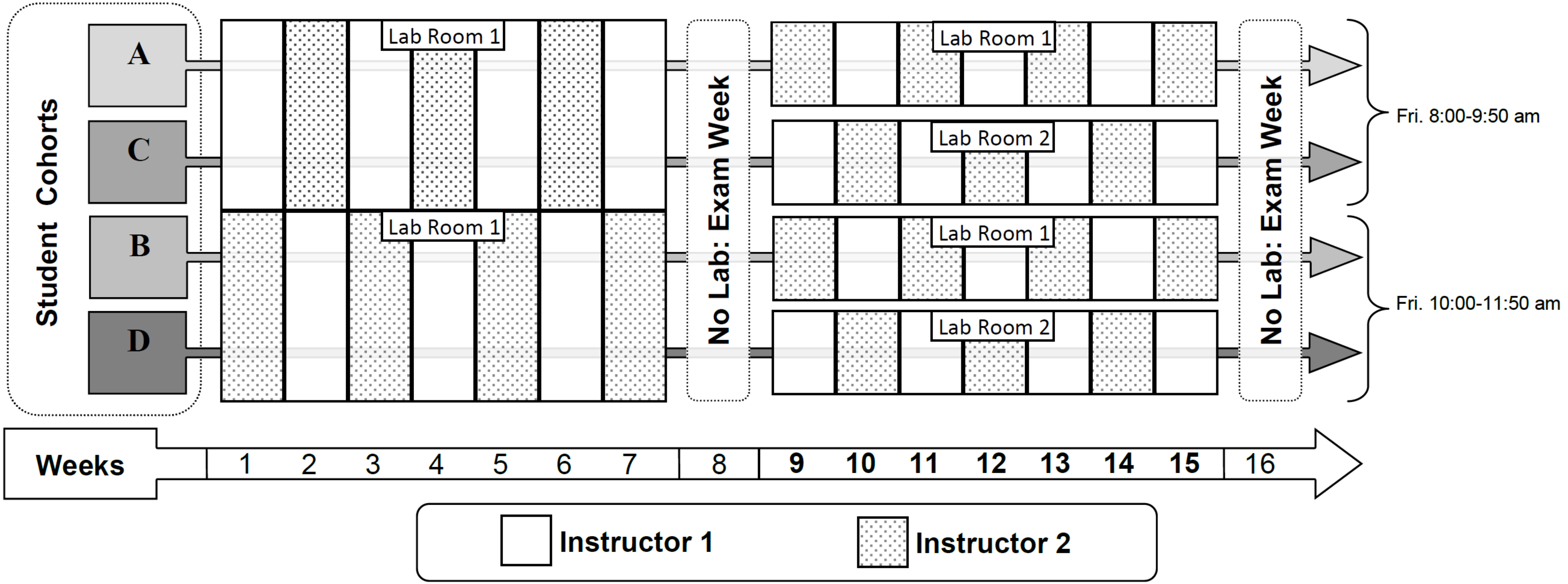
Curricula Topic Timeline



Lecture Classroom Schedule



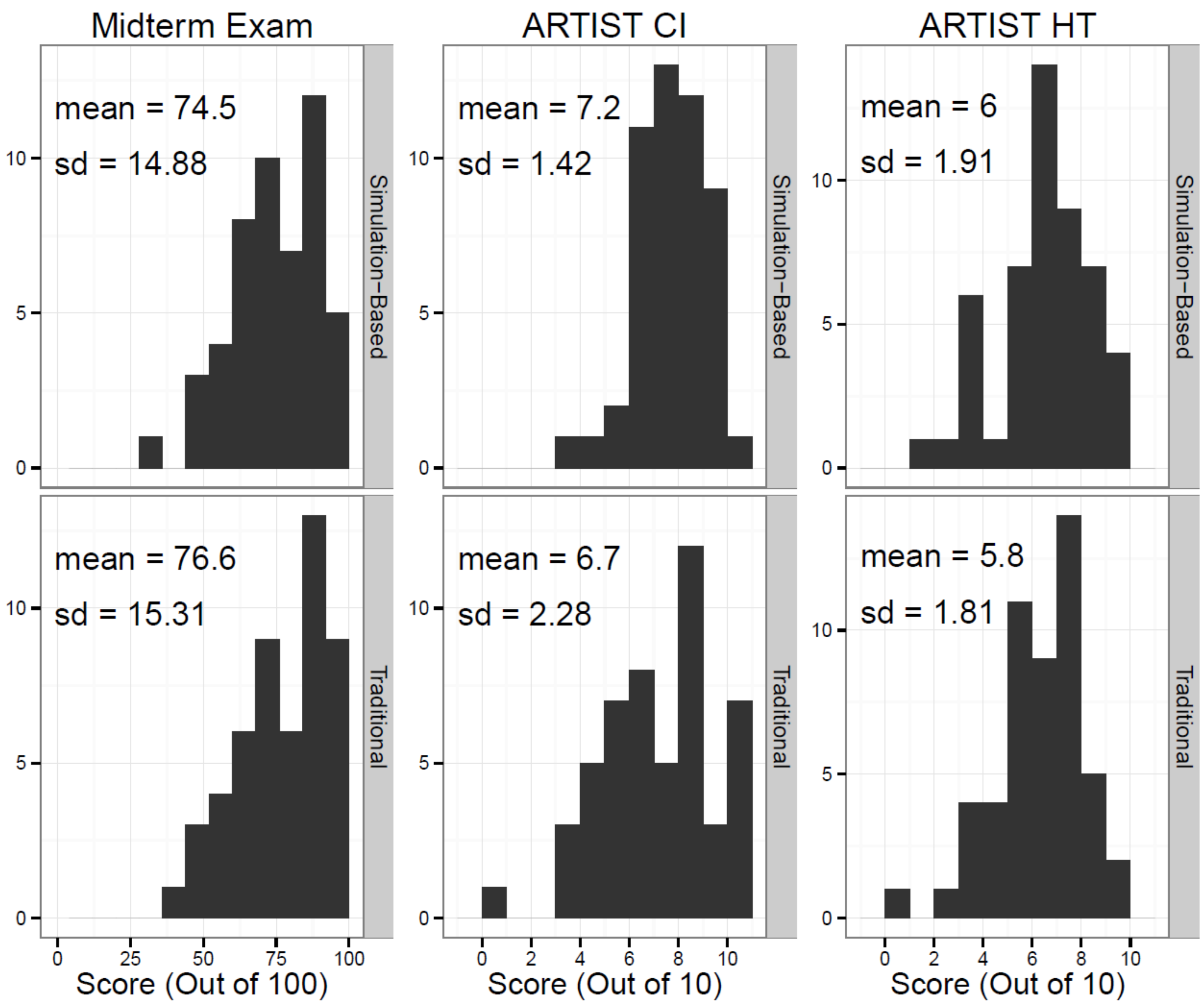
Lab Classroom Schedule



Data Collection

- Course Administration
  - Inference Curriculum Treatment
  - Enrollment Section
- Pre-Treatment Measures
  - Homework 1-7 Scores
  - Lab 1-7 Scores
  - Midterm Exam Score
- Learning Outcomes: ARTIST scaled question sets
  - Hypothesis Testing (HT score)
  - Confidence Intervals (CI score)

Student Scores by Curricula



Linear Model for Student Learning Scores

$$y_{i\ell} = \tau_\ell \mathbb{1}_{\{i \in T\}} + \beta_{\ell 0} + \sum_{p=1}^{P} x_{ip}\beta_{\ell p} + \epsilon_{i\ell},$$

where

$y_{i\ell}$	is the ℓ^{th} response ($\ell \in \{1, 2\}$) from student i, $1 \leq i \leq n$,
τ_ℓ	is the treatment effect of the simulation-based curriculum on response ℓ, and
$\mathbb{1}_{\{i \in T\}}$	is the indicator function for student i in the treatment group.
$\beta_{\ell 0}$	is the common intercept for response ℓ, and
$\beta_{\ell p}$,	$1 \leq p \leq P$ are the model coefficients of the P covariates.
x_{ip}	is the p^{th} pre-treatment covariate score of student i, and
$\epsilon_{i\ell}$	is the error for the ℓ^{th} response from the i^{th} student.

We assume that error pairs are independent and identically distributed:

$$\vec{\epsilon}_i = \begin{bmatrix} \epsilon_{i1} \\ \epsilon_{i2} \end{bmatrix} \overset{iid}{\sim} \text{MVN}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Sigma = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 \end{bmatrix} \right)$$

Effect Size Inference

	Covariate Values	HT coefficient (SE)	CI coefficient (SE)
Intercept :	-	**2.1053 (1.0584)**	1.4648 (1.0135)
Midterm :	0,1,…,100	**0.0386 (0.0118)**	**0.0477 (0.0113)**
Lab 5 :	0,1,…,100	0.8547 (0.6618)	**1.8274 (0.6337)**
Treatment :	0 = Traditional 1 = Sim. Based	0.3050 (0.3532)	**0.7146 (0.3382)**

***Bold** indicates a significant effect at the $\alpha = 0.05$ level

The "iid" problem

The experimental design makes causal conclusions about the results foolproof… right?

- Randomized students to treatments
- Alternating to spread out instructor effects
- Controlling environment to be as similar as possible

Our model assumed iid bivariate normal error vectors

- Treatments not applied independently, curriculum applied to cohorts

Bending a model assumption may seem innocuous

Simulation study conducted shows that

1. If independence is violated with constant covariance between all students, then Type I error holds
2. If independence is violated with stronger covariance between classmates, then Type I errors inflate

* Note: this is a pervasive problem in assessment of educational practices

Conclusions

Model-Based Results:

- Randomization-based inference curriculum had a significant improvement on confidence interval related learning outcomes
  - 7% improvement for Confidence Interval concepts (significant) on the ARTIST scale
  - 3% improvement for Hypothesis Test concepts (*not* significant) on the ARTIST scale

Discussion:

- Population – Ag/Bio undergrads at Midwestern land-grant university
- Simulation study on the violation of “iid” errors shows real concern of Type I error
- Viewed as a case study: *We* saw improvements to student learning outcomes on inference topics under the simulation-based curriculum
- As instructor, it was enjoyable to teach the simulation-based curriculum
  - Student engagement, leveraging technology, concepts first then mathematical detail

Acknowledgements

Study advisors:

Dr. Heike Hofmann

Dr. Bob Stephenson

Thank You

Questions?

For full study detail and references see article in TISE

http://escholarship.org/uc/item/0wm523b0

Supplemental Slides
(In case of audience questions, break glass)

Simulation Study Results
Independence Violation

Simulate using generative model with *no treatment effect,* and a covariance structure that violates independence

Generative Model:

$$y_{ijk\ell} = [\beta_{0k} + x_{ijk1}\beta_{k1} + x_{ijk2}\beta_{k2}] + [\eta_\ell + \gamma_{k\ell} + \delta_{jk\ell} + \epsilon_{ijk\ell}]$$

$$\vec{\epsilon}_{ijk} = \begin{bmatrix}\epsilon_{ijk1}\\ \epsilon_{ijk2}\end{bmatrix} \overset{iid}{\sim} \text{MVN}\left(\begin{bmatrix}0\\0\end{bmatrix}, \Sigma = \begin{bmatrix}\sigma_{11}^2 & \sigma_{12}^2\\ \sigma_{21}^2 & \sigma_{22}^2\end{bmatrix}\right),$$

$$\vec{\delta}_{jk} = \begin{bmatrix}\delta_{jk1}\\ \delta_{jk2}\end{bmatrix} \overset{iid}{\sim} \text{MVN}\left(\begin{bmatrix}0\\0\end{bmatrix}, d\Sigma = \begin{bmatrix}d\sigma_{11}^2 & d\sigma_{12}^2\\ d\sigma_{21}^2 & d\sigma_{22}^2\end{bmatrix}\right),$$

$$\vec{\gamma}_k = \begin{bmatrix}\gamma_{k1}\\ \gamma_{k2}\end{bmatrix} \overset{iid}{\sim} \text{MVN}\left(\begin{bmatrix}0\\0\end{bmatrix}, g\Sigma = \begin{bmatrix}g\sigma_{11}^2 & g\sigma_{12}^2\\ g\sigma_{21}^2 & g\sigma_{22}^2\end{bmatrix}\right),$$

$$\vec{\eta} = \begin{bmatrix}\eta_1\\ \eta_2\end{bmatrix} \overset{iid}{\sim} \text{MVN}\left(\begin{bmatrix}0\\0\end{bmatrix}, z\Sigma = \begin{bmatrix}z\sigma_{11}^2 & z\sigma_{12}^2\\ z\sigma_{21}^2 & z\sigma_{22}^2\end{bmatrix}\right).$$