

# Rolling the Dice: Flipping an elementary probability and statistics classroom

Jerry Orloff and Jonathan Bloom

Mathematics Department and Broad Institute, MIT

*jorloff@math.mit.edu*   *jbloom@broadinstitute.org*

Support from the Davis Foundation  
and PI/visionary Haynes Miller

Sept. 26, 2017

# Overview

- 1 What we inherited
- 2 What we created
- 3 Demonstration
- 4 What we learned
- 5 Syllabus (if time)

# What we inherited

18.05: Introduction to probability and statistics.

- Traditional lecture class for non-math majors
- Dwindling enrollment

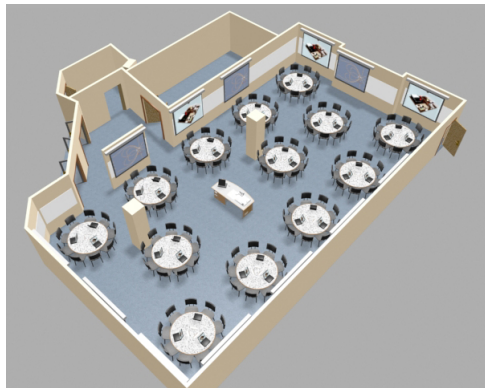
An interest in new approaches.

- active learning (Haynes Miller)
- online learning (the world)

# Transition

- New classroom
- New pedagogy
- New technology
- New curriculum (at the end if time)

# Room and video



[Show video clip, full video on OCW 18.05 site (link below)]

## Active learning, flipped classroom

- Meet 3 x 80min in TEAL room
- 60 students, 2 teachers, 3 assistants
  
- Reading / reading questions on MITx
- Minimal lecturing
- Group problem solving at boards
- Whole class and table discussions
- Clicker questions
- Computer-based studio using R
- Traditional psets and pset checker

# Bayesian dice



# Bayesian dice



2



# Bayesian dice



21

# Bayesian dice



2 1 6

# Bayesian dice



2 1 6 5

# Bayesian dice



2 1 6 5 8

# Bayesian dice



2 1 6 5 8 7 3 2 7

# Bayesian dice



2 1 6 5 8 7 3 2 7 3 6 5 6

# Bayesian dice



2 1 6 5 8 7 3 2 7 3 6 5 6 4 8 8 6 7  
 8 7 5 1

## Active learning notes

- Standing up is beneficial
- Physical space is critical
- Both peer and teacher instruction
- Student self-assessment
- Teachers formative assessment
- Accelerates learning to teach content

Coming soon: EMES talk by David Pengelley on how to flip a class.



# Technology and flipped classroom

- Reading questions
- Attendance
- Pset checker

# Computer studio

- Once a week
- Used R
- Don't teach programming. Let students do it!
- Heavily scaffolded projects designed to reinforce concepts
- Graded –need efficient grading system
- Tested –open internet
- Took about 3 years to get a good set of projects

## Common questions

How much work was all this?

- A tremendous amount, especially at first, because we changed so many things at once.
- Using MIT<sub>x</sub> added some overhead and requires someone willing to fight with it.
- Much less work by the third year.

How much are you able to cover?

- More material with greater understanding.

## Other observations

- Active learning is more fun
- Co-teaching is more fun
- Students like getting to know their teachers
- Students like targeted reading more than lecture video
- Students love the pset checker

# OpenCourseWare and OCW Educator

All 18.05 course materials and a discussion of the pedagogy and educational decisions is on OCW:

`https://ocw.mit.edu/courses/mathematics/  
18-05-introduction-to-probability-and-statistics-spring-2014/`

## Broad Course Goals

- Learn the language and core concepts of probability theory
- Understand basic principles of statistical inference (Bayesian, frequentist, bootstrap)
- Build a starter statistical toolbox with appreciation for both utility and limitations
- Use software and simulation to do statistics (R).
- Become an informed consumer of statistical information (paper analysis).
- Prepare for further coursework or on-the-job study (active learning).

# Curriculum

Traditional course:

- Probability: counting, random variables, gallery of distributions, central limit theorem.
- 

- Statistics: linear regression, estimation, confidence intervals, p-values, NHST, bootstrapping

Changes:

- A Bayesian bridge
- Heavy use of computers for simulation and visualization

# The fork in the road

**Probability  
(mathematics)**

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)}$$

Everyone uses Bayes' formula when the prior  $P(H)$  is known.

Bayesian path

Frequentist path

**Statistics  
(art)**

$$P_{\text{Posterior}}(H|D) = \frac{P(D|H)P_{\text{prior}}(H)}{P(D)}$$

Bayesians require a prior, so they develop one from the best information they have.

$$\text{Likelihood } L(H; D) = P(D|H)$$

Without a known prior frequentists draw inferences from just the likelihood function.



## Course Arc

- Probability:  
(uncertain world, perfect knowledge of the uncertainty)
  - Basics of probability: counting, independence, conditional probability
- Statistics I: pure applied probability:  
(data in an uncertain world, perfect knowledge of the uncertainty)
  - Bayesian inference with known priors
- Statistics II: applied probability:  
(data in an uncertain world, imperfect knowledge of the uncertainty)
  - Bayesian inference with unknown priors
  - Frequentist confidence intervals and significance tests
  - Resampling methods: bootstrapping
  - Discussion of scientific papers
- Computation, simulation and visualization using R and Javascript applets were used throughout the course.

Thank you

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