Sequential Randomization to Develop Personalized and Optimized Interventions in Massively Open Online Courses: A Case Study

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Overview

- Describe sequentially randomized trials (SRTs)
- Show why SRTs are useful
- Exemplify SRTs through a case-study (with results!)

Work available on arXiv:

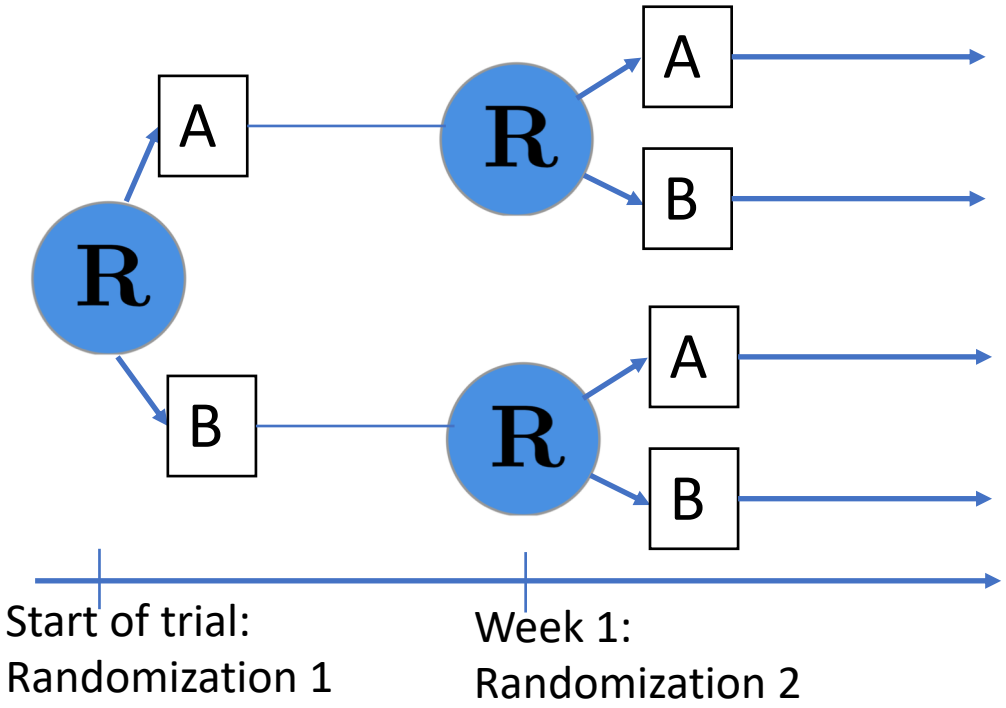
T. NeCamp, J. Gardner, C. Brooks, “Beyond A/B Testing: Sequential Randomization for Developing Interventions in Scaled Digital Learning Environments”. Oct 2018.

Sequencing, Timing, and Personalizing Interventions

- In digital environments:
  - Many intervention options are available
  - Interventions delivered quickly and frequently
  - Large diversity of users
- In this setting, questions arise about:
  - 🔄 **Sequencing**: What is the best order of interventions to deliver?
  - ⏱ **Timing**: At what times are certain interventions most effective?
  - 👥 **Personalizing**: For whom are certain interventions more effective?

What are Sequentially Randomized Trials?

- SRTs explore sequencing, timing, and personalization.
- In SRTs, individuals are randomized multiple times

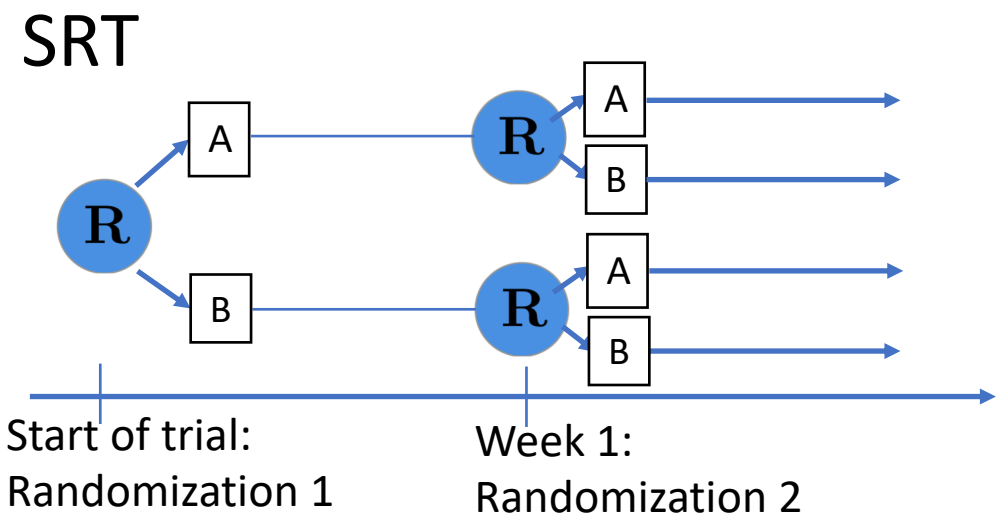


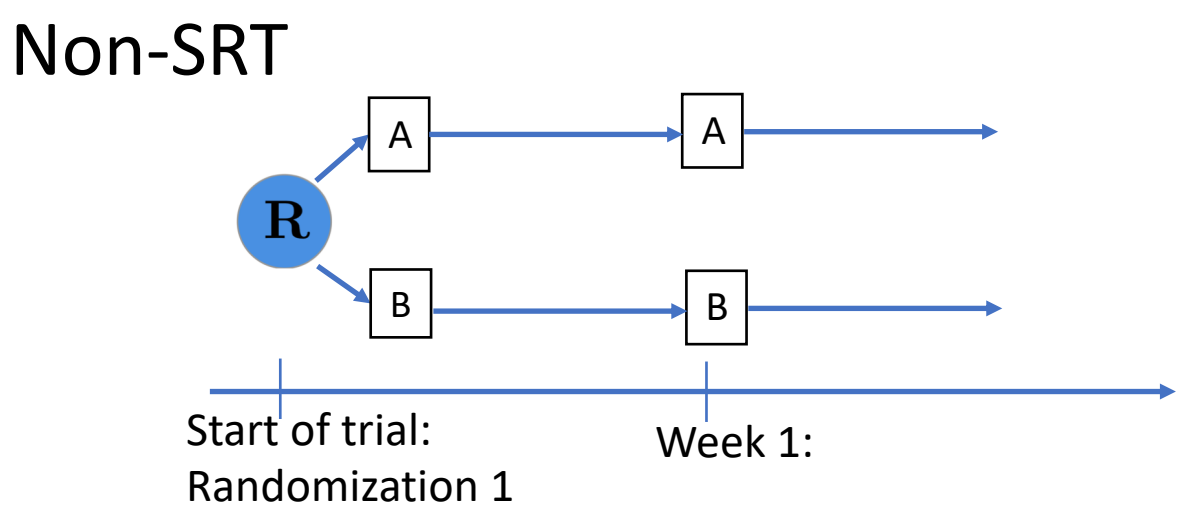
Modification of the simple SRT

- Two common SRT designs:
  - Sequential Multiple Assignment Randomized Trials (Murphy, 2005)
  - Micro-randomized trials (Klasnja, 2015)

Advantages of SRTs: Sequencing of interventions

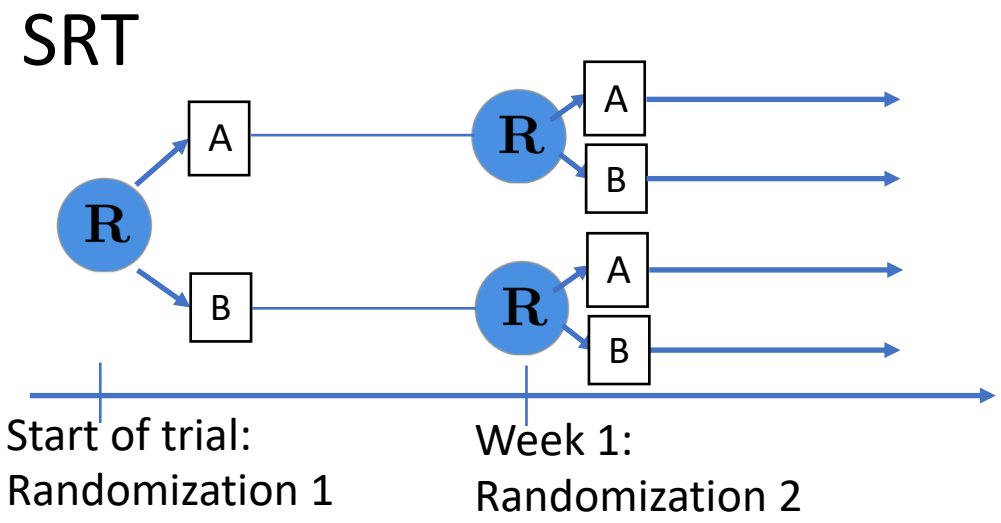
- SRT data can be used to compare a larger variety of sequences

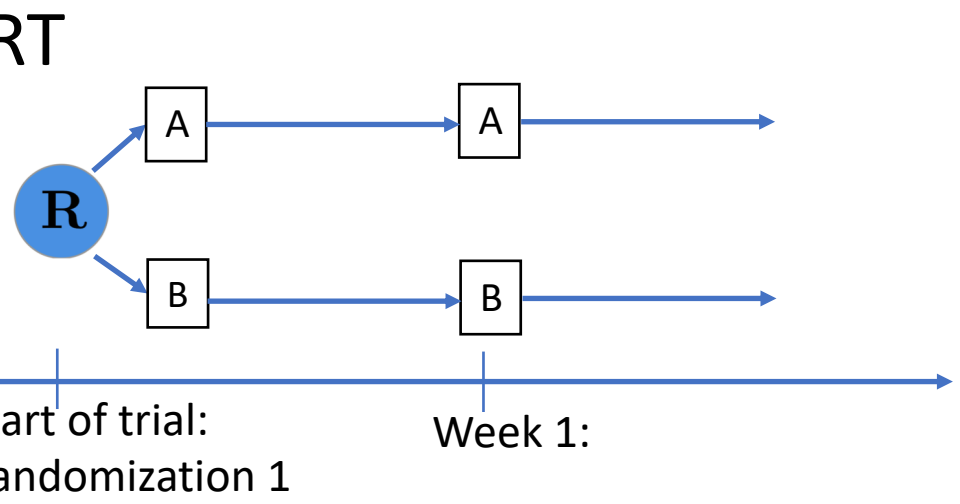




Advantages of SRTs: Timing of interventions

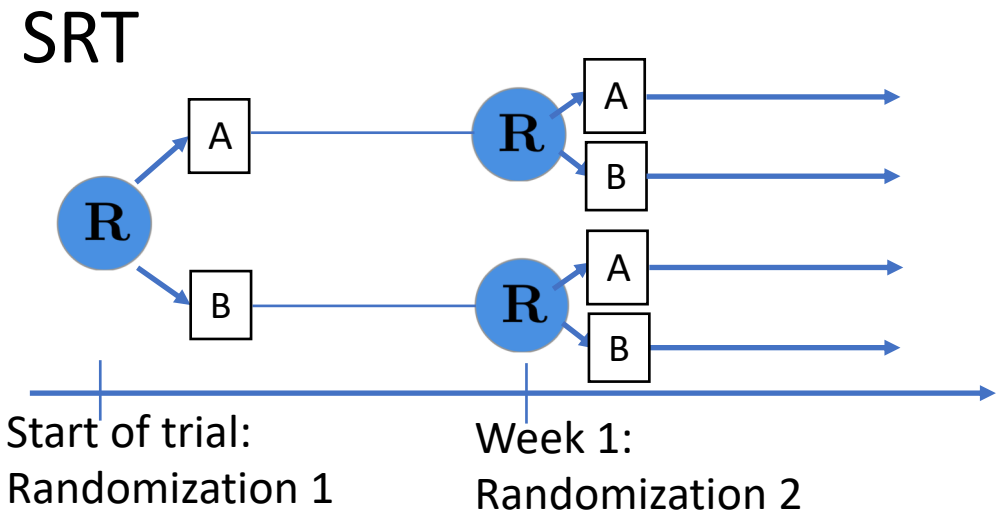
- SRTs provide data to evaluate interventions at various time points

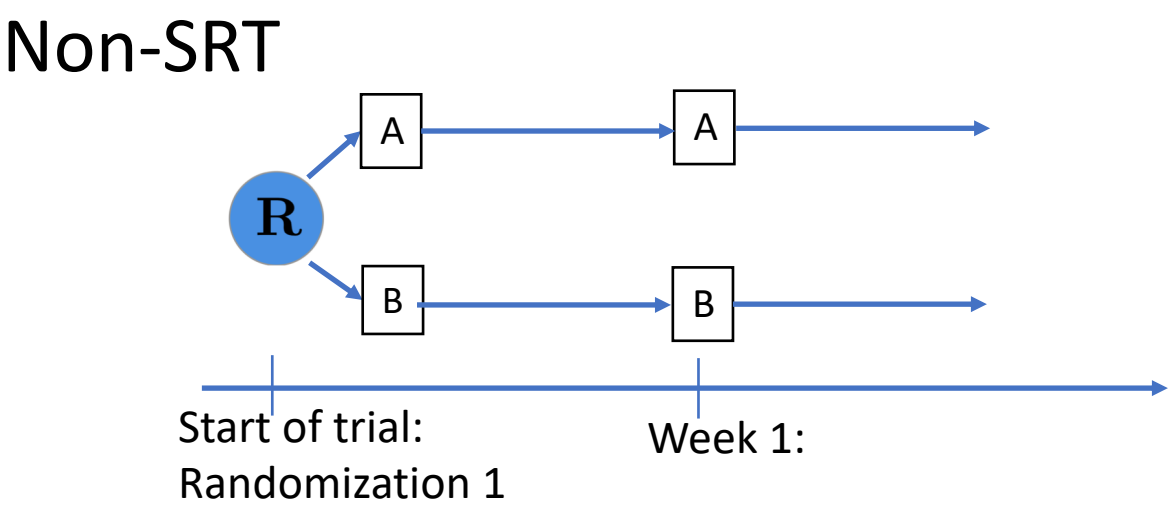




Advantages of SRTs: Personalizing interventions

- SRTs can be used to discover how to personalize based on data collected during the trial





Case study: An SRT in a digital learning environment

- Massively Open Online Courses (MOOCs) are digital environments for online learning
- Low completion rates are a well-known issue in MOOCs
- **Goal: Design a weekly email intervention to reduce dropout with**
  - A culturally relevant data science problem
  - Psychological framing (i.e., growth mindset)

7 email types =
2 psychological framings x 3 problem types +
1 no email

Email	No-Growth Mindset	Growth Mindset
No Problem Email		
Global Problem Email		
Cultural Problem Email		

No Email

As a learner in India, you might find this problem interesting. In recent years, renewable power generation in India has been on the rise. Due to different resources and policies, there are big differences in state level energy production. What are the top 5 Indian states generating the most renewable power per capita? To answer this question, this week, you will learn to merge two DataFrames together.

Learn how to merge DataFrames and view the course videos on the Coursera course.

Copy and paste the code into a new Jupyter notebook to give it a try!

Link to code

Merging DataFrames is not easy. Keep in mind that we can all learn to solve data science problems if we practice and persevere. If you want to see how I solved the problem, check out my code.

Motivating Research Questions

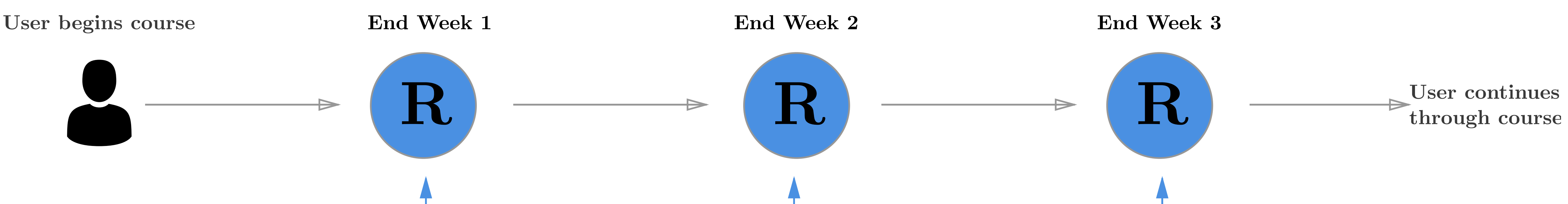
🔄 **Sequencing:** Which sequence of emails most improves course activity in later weeks?

⏱ **Timing:** Which email problem type is most effective, on average, for bringing learners back to the course during each week?

👥 **Personalizing:** Are certain data science problem emails more or less effective for active learners?

To answer these questions we designed…

Trial design and randomization probabilities



End Week 1

Email	No-Growth Mindset	Growth Mindset
No Problem Email	0.14	0.14
Global Problem Email	0.14	0.14
Cultural Problem Email	0.14	0.14

No Email	0.14

End Week 2

Email	No-Growth Mindset	Growth Mindset
No Problem Email	0.14	0.14
Global Problem Email	0.14	0.14
Cultural Problem Email	0.14	0.14

No Email	0.14

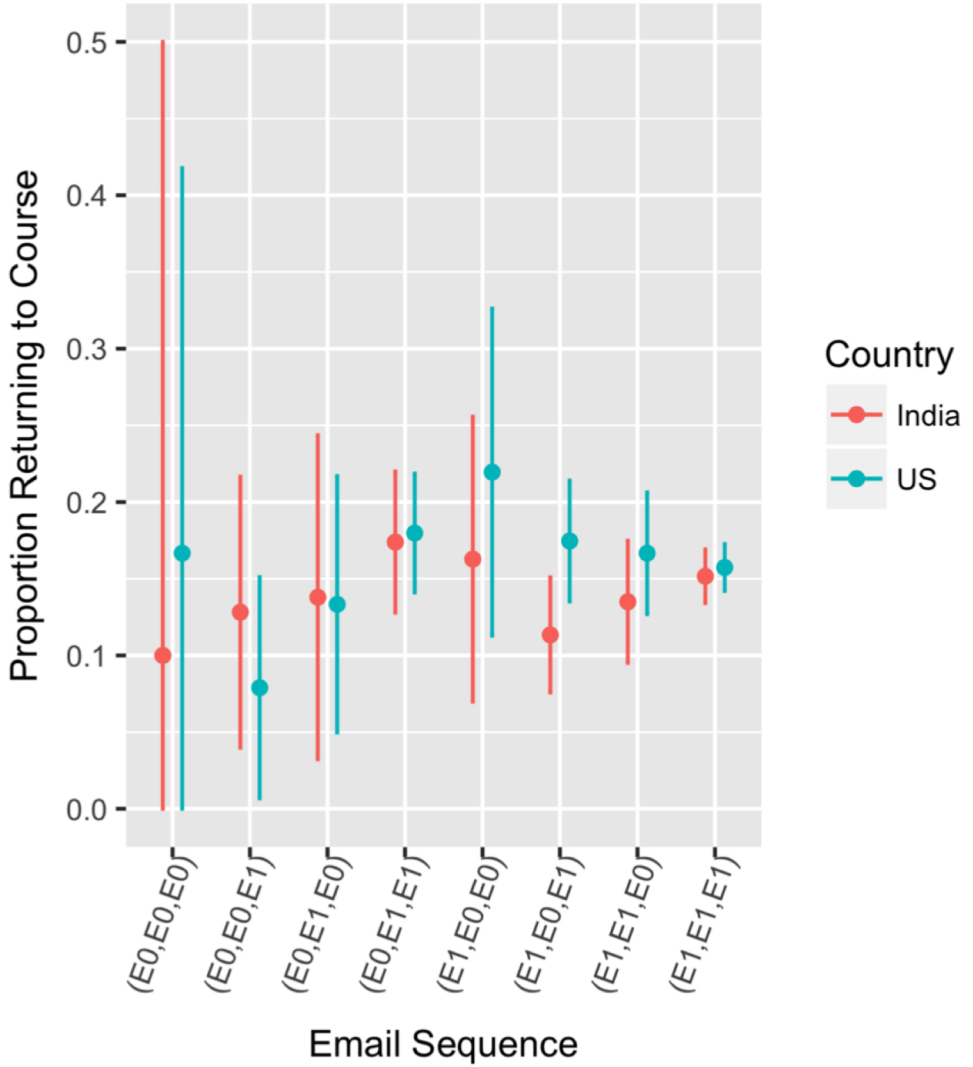
End Week 3

Email	No-Growth Mindset	Growth Mindset
No Problem Email	0.14	0.14
Global Problem Email	0.14	0.14
Cultural Problem Email	0.14	0.14

No Email	0.14

Sequencing of the email intervention

Compare sequences of emails (E1) and no emails (E0)

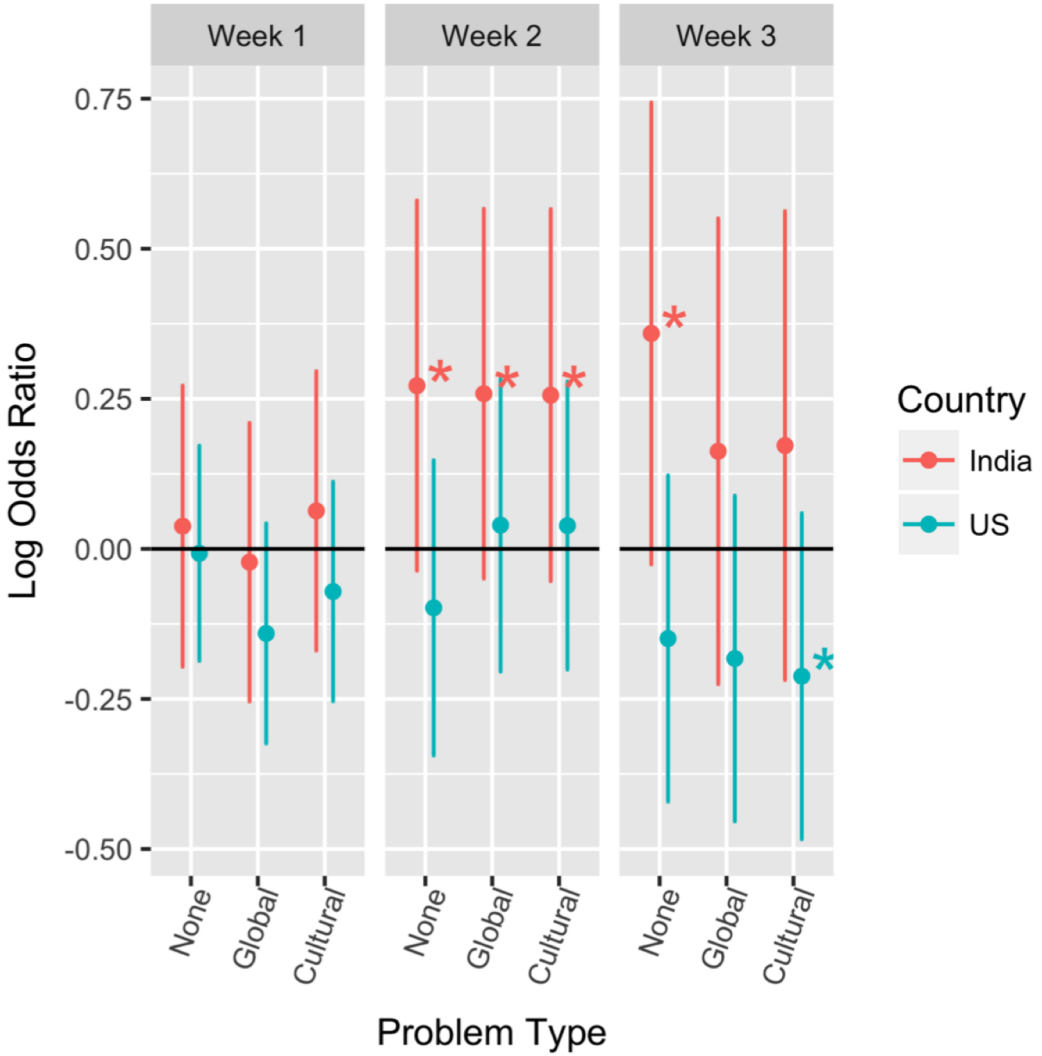


We find:

- US learners like sequences with emails in first week
- Sequence effects are weak for both learners

Timing of the email intervention

Compare effect of email types at various weeks on propensity to return to the course

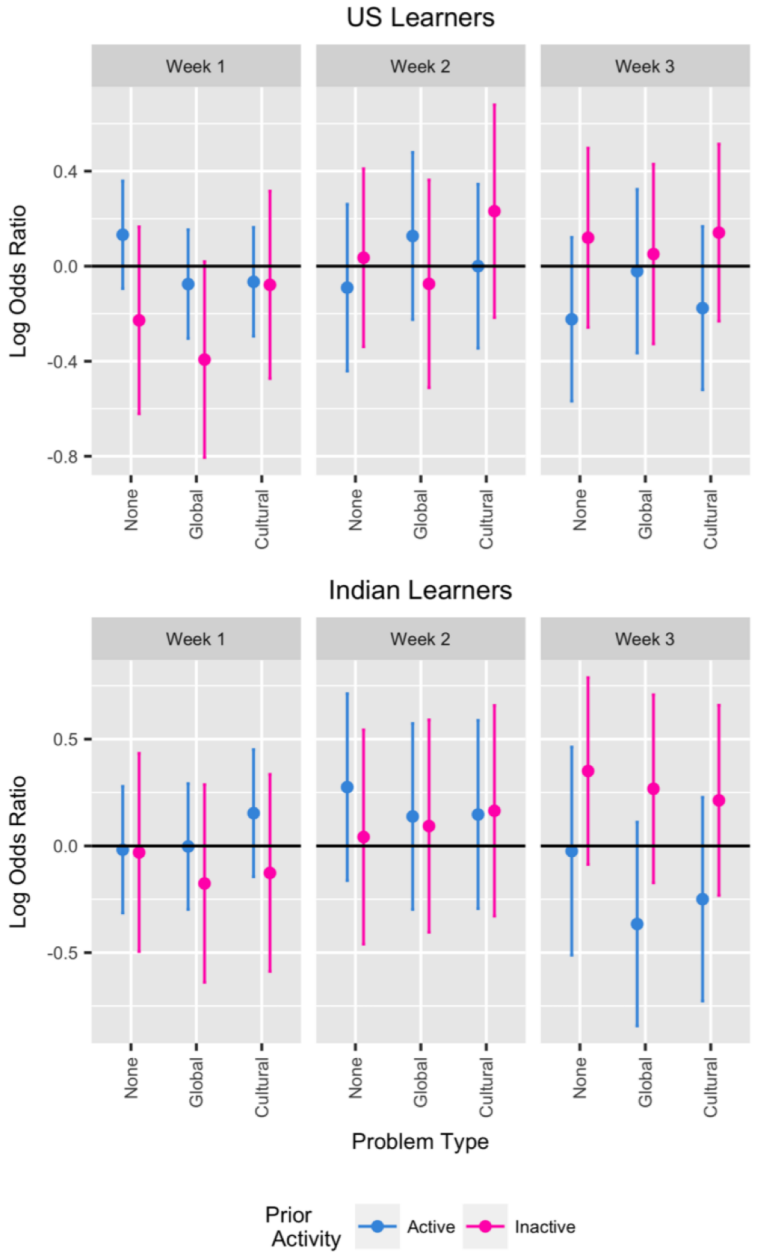


We find:

- Indian learners benefit in weeks 2 and 3, but nothing added from global or cultural problems
- Email effect minimal for US learners

Personalizing of the email intervention

Compare email efficacy for active/inactive users during previous week



We find:

- In week 1, for both US and Indian learners, emails performed better for active users
- In week 3 emails performed better for inactive users
- Positive effects for inactive users but negative for active users

Trial takeaways and future work

- Emails were more effective for Indian than US learners
- Including (relevant) data science problems did not make a difference
- Active learners prefer emails at the beginning and inactive learners prefer emails at the end

- Next steps: Develop a personalized email intervention sequence and evaluate it’s efficacy in an A/B test

References

- T. NeCamp, J. Gardner, C. Brooks, “Beyond A/B Testing: Sequential Randomization for Developing Interventions in Scaled Digital Learning Environments”. Oct 2018.
- P Klasnja, EB Hekler, S Shiffman, A Boruvka, D Almirall, A Tewari, and SA Murphy. 2015. Microrandomized trials: An experimental design for developing just-in-time adaptive interventions. Health Psychology 34, (2015), 1220.
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Thank you!

Questions?