Communication at Scale in a MOOC Using Predictive Engagement Analytics

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Paper link: http://tiny.cc/**aied_communication_paper**




AIED 2018

Berkeley | EECS
Electrical Engineering and Computer Sciences

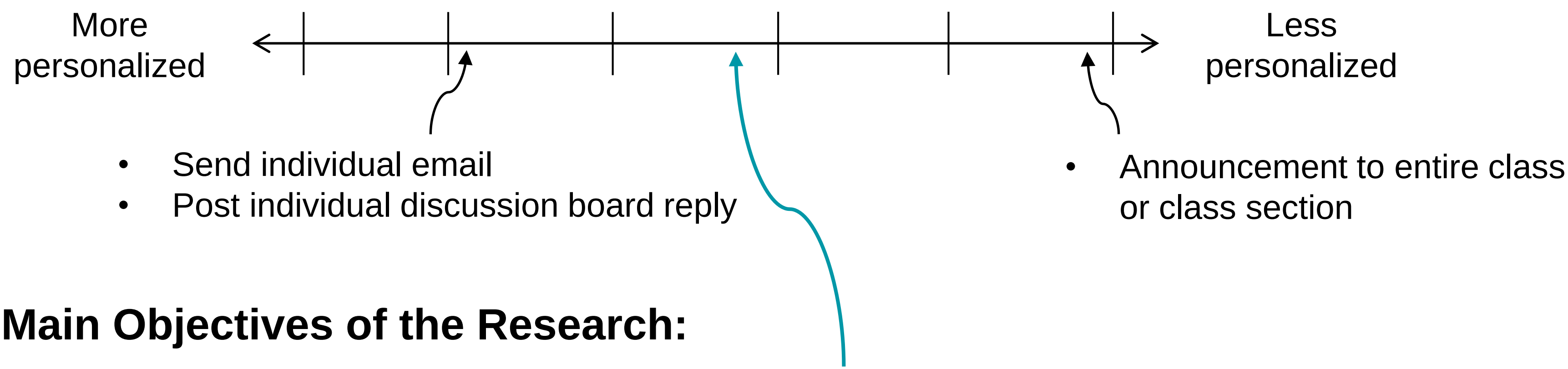
CAHL Computational Approaches to Human Learning (CAHL) research lab

Graduate School of Education

UC Berkeley School of Information

One-on-one instructor communication scarce in “at scale” classrooms

Communication options for online instructors:



Main Objectives of the Research:

1. Provide instructors an intermediary level of personalized communication based on learners’ engagement analytics

2. Deploy a working instructor communications interface in an edX course with daily updated analytics as proof-of-concept

Related work on engagement (drop-out)

Drop-out interventions

- Drop-out survey as unintentional intervention (Whitehill et al., 2015)
- Peer social chat within a course (Ferschke, 2015)
- Early warning course drop-out system on-campus (Jayaprakash, 2014)

Drop-out prediction models

- Hidden Markov Models (Balakrishnan & Coetzee, 2013)
- Support Vector Machines (Kloft et al., 2014)
- Logistic regression (Jiang et al., 2014)
- Recurrent Neural Networks (Mi & Yeung, 2015) hand-engineered features
- Ensembles (Boyer & Veeramachaneni, 2016)

Drop-out model frameworks for evaluation/replication

- Drop-out prediction replication frameworks (Andres et al., 2017;Gardner & Brooks, 2018)

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Additional Note on Motivation

“What good is prediction?”
(asked yesterday)

We argue that making predictive models useable in real-world contexts is as valuable an endeavor for the AIED community as is discovery and data mining with those models

Drop-out prediction models

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Our Methodology

1. **Evaluate past predictive models** + RNNs (with representation learning) on a large course dataset

2. **Build an analytics backend API and front-end interface** for the communications dashboard

3. Using the best predicting modeling approach from the evaluation to provide actionable engagement analytics in the dashboard for a **deployment** course

Dataset

- Began with 102 edX MOOCs offered between 2015-2016
- Filtered by the following:
  - Instructor-paced only (checked via course descript & deadlines)
  - At least 100 certified (passed) learners
- This resulted in 21 courses, with one outlier having 3x the number of certified (removed)
- Final set was 20 courses with 13.6 million clickstream events total

Dataset

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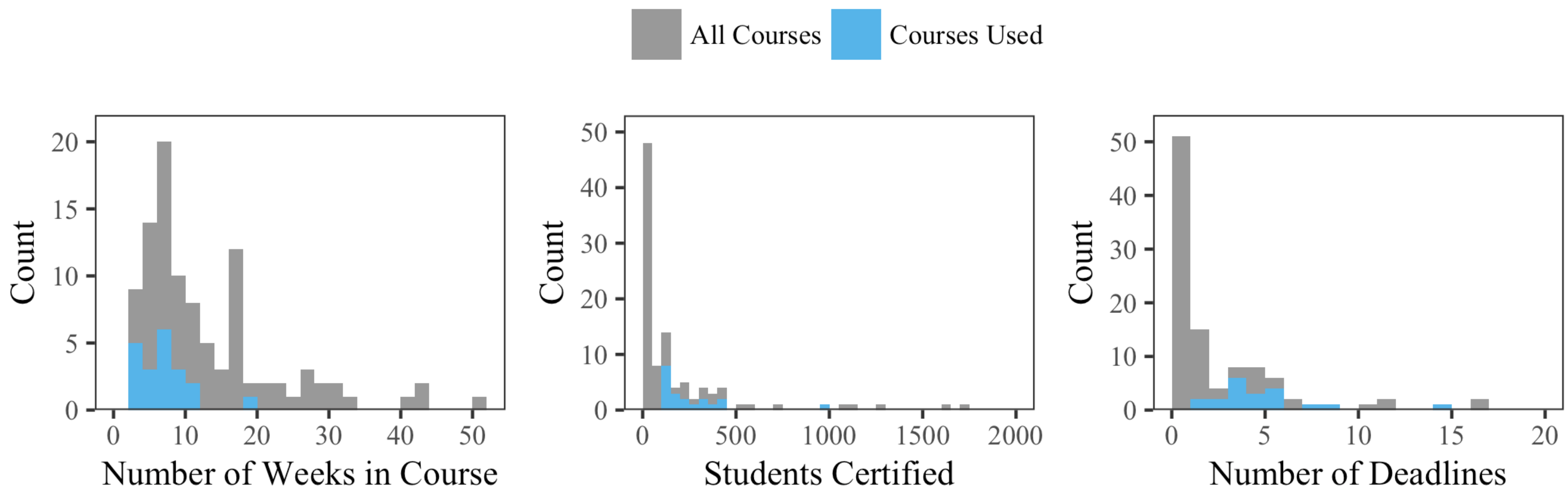
Comparison of distributions between the original 102 courses and the selected 20



Descriptive statistics for the selected 20 courses

Duration (weeks)			**Unique Deadlines**			**Certified Students**		
Min	Median	Max	Min	Median	Max	Min	Median	Max
4	7.7	19	2	4.5	15	102	189.5	958

Prediction Models Evaluated

1. LSTM (with hand-engineered features)
2. LSTM (representations learned from clickstream)
3. K-Nearest Neighbors
4. Logistic Regression
5. Random Forests
6. Ensemble (of models 3-5)

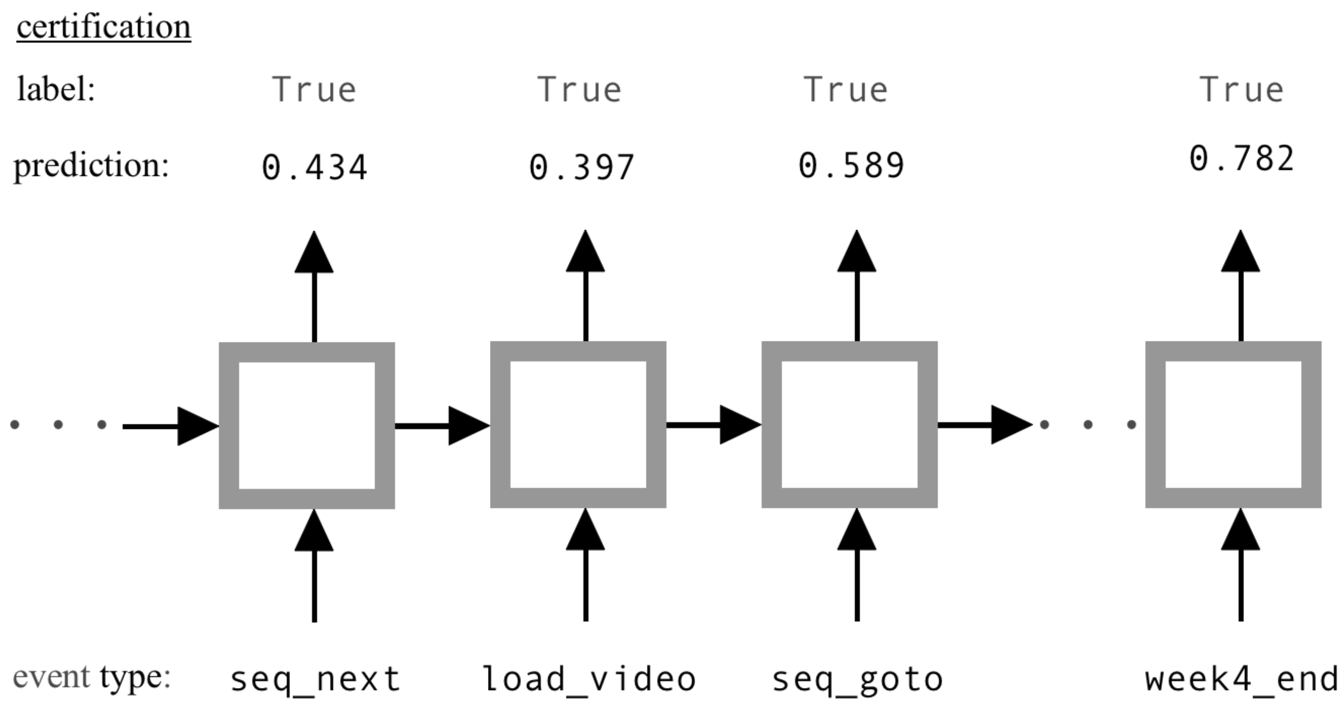
A set of 12 hand-engineered features were used

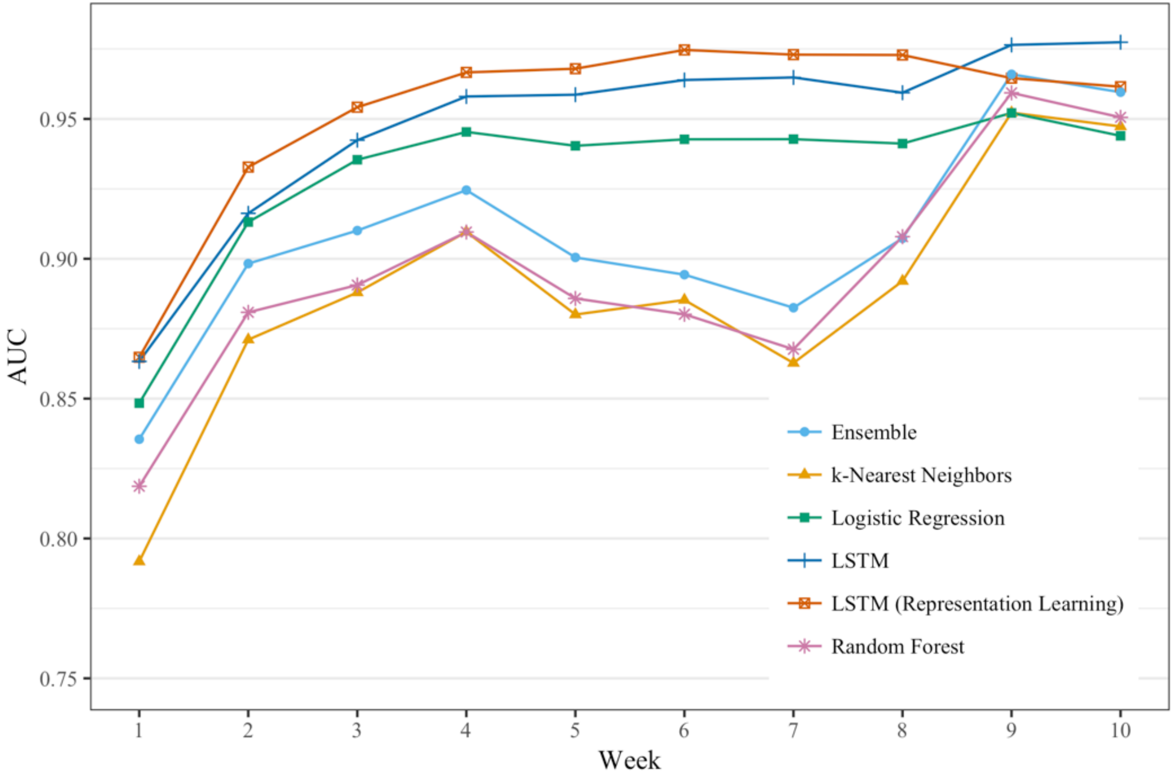
Prediction Models Evaluated

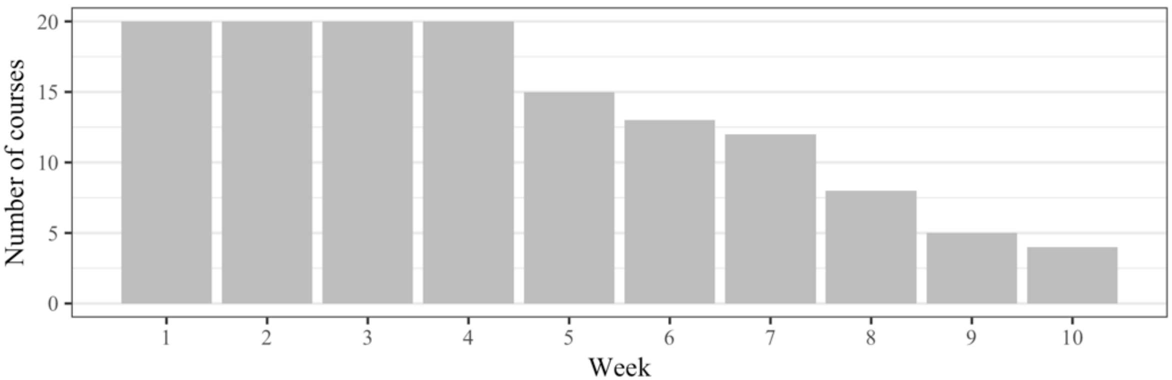
Hand-engineered feature set

1. Total time[3] spent on learning resources[4]	**7**. Average time difference between submitting a problem and its respective deadline
2. Number of distinct problems attempted	**8**. Duration of the longest-observed learning event
3. Average number of attempts per problem	**9**. Total time spent on video lectures
4. Number of distinct correct problems	**10**. Standard deviation of duration of learning events
5. Ratio of total time spent on learning resources to number of correct problems	**11**. Ratio of number of attempted problems to number of correct problems
6. Total time since last student action	**12**. Percent time through a course

LSTM Model Inputs and Outputs
(representation learning version)



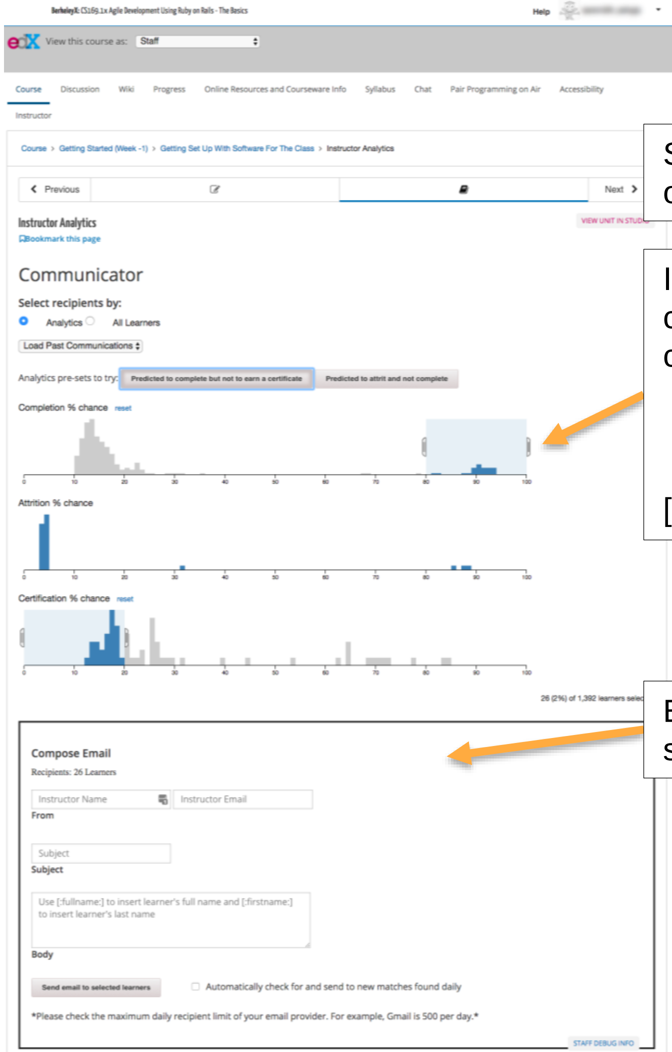




Prediction Results

- 5-fold cross-validation
(16 courses training, 4 testing)
- LSTM with representation learning outperformed all other approaches except for last two weeks ($p < 0.05$)
- Logistic regression better than non-RNN methods (including Ensemble)
- LSTM (representation learning) used for additional drop-out and completion outcome prediction models

Dashboard (front-end) Design



Student engagement analytics displayed on staff only viewable dashboard

Instructor selects learners to communicate with based on analytics consisting of per-student predictions of:

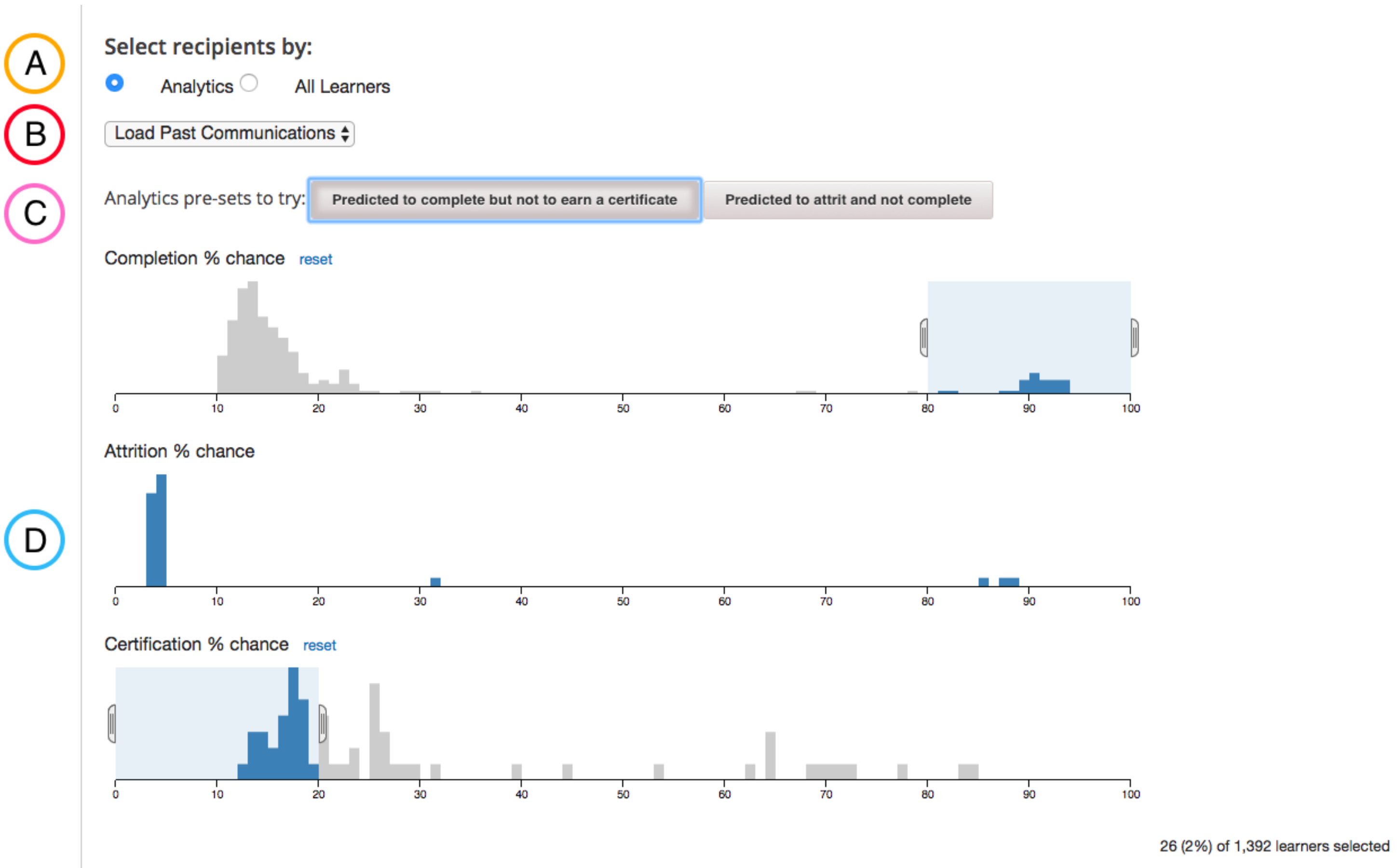
- Completion
- Attrition
- Passing/Certification

[*generated from daily edX event logs*]

Email composed and sent to selected learners

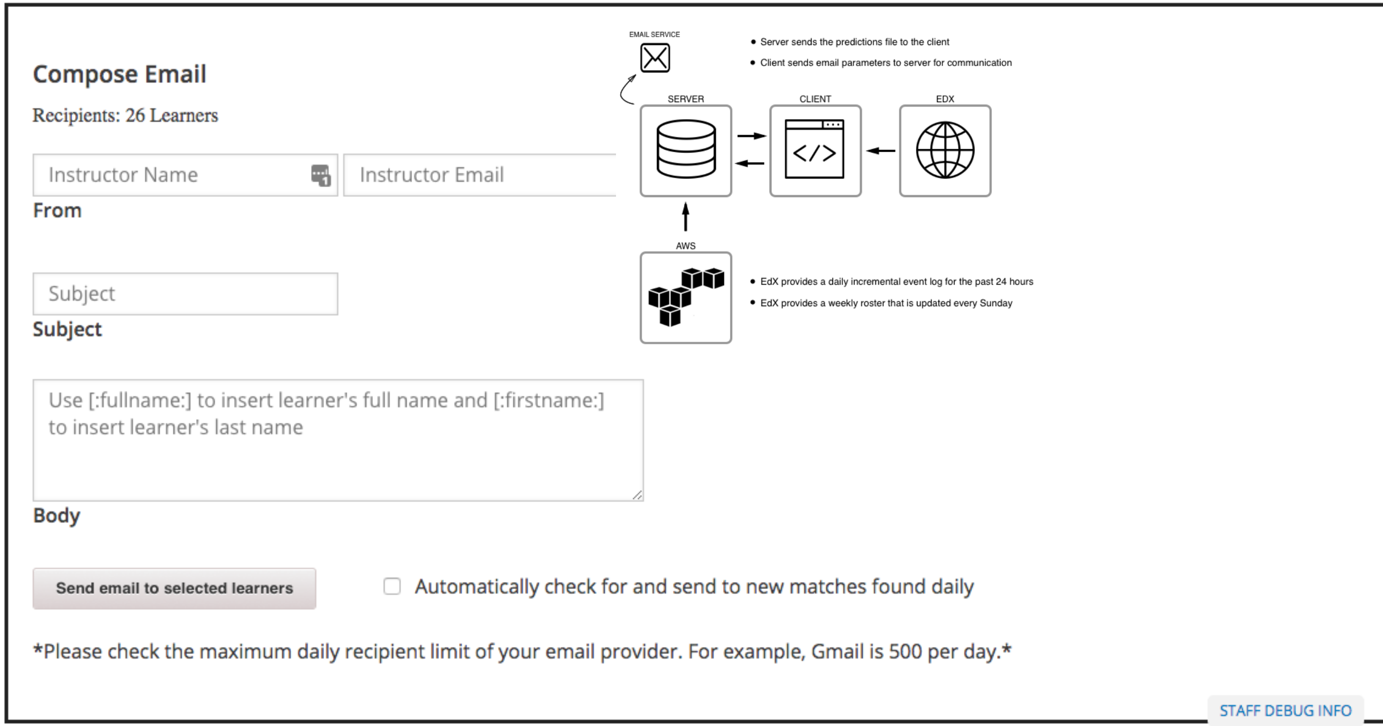
DEMO

Selection of recipients based on engagement analytics



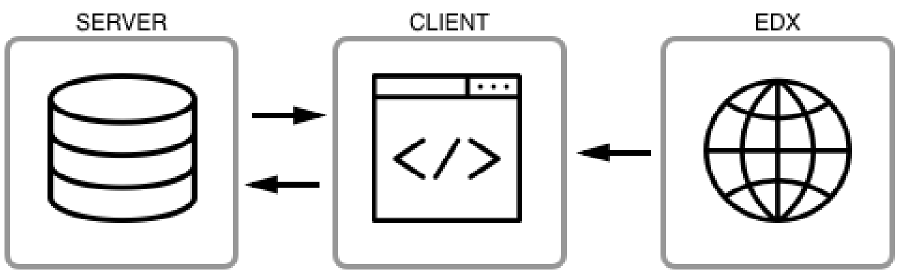
Composition of email to selected recipients

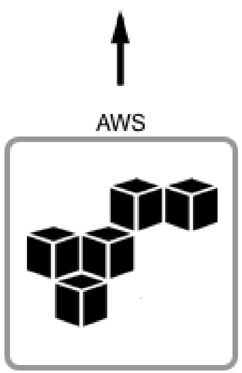
E



Engagement Analytics (back-end) API

- Server sends the predictions file to the client
- Client sends email parameters to server for communication



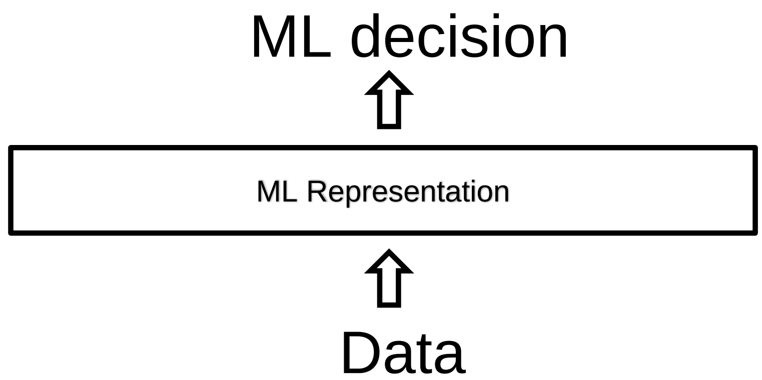


- EdX provides a daily incremental event log for the past 24 hours
- EdX provides a weekly roster that is updated every Sunday

Replication requirements

edX data assets	COMMUNICATOR
Staff course access to edX studio to insert dashboard html into vertical	X
Daily event log from deployment course e.g. *berkeleyx-events-2018-06-05.log.gz*	X
Weekly roster from deployment course e.g. *BerkeleyX-CS169.2x-1T2018-auth_user-prod-analytics.sql*	X

Reflection on the role of AI in Education



Reflection on the role of AI in Education

Intervention

⇧

Human interpretation

~~ML decision~~

⇧

ML Representation

⇧

Data

- Human-AI interaction
- Intelligence Amplification (IA) instead of AI
- Human-in-the-loop

Contributions

- Features learned automatically (via representation learning) more effective than ensemble models using our 12 hand-engineered features
- Demonstration of making MOOC prediction models actionable in the real-world
- Publicly available “end-to-end” code base for full replication

Future Uses of the Communicator

- Instructor personalized communications based on
  - Common wrong answers to a particular question
  - Scores on an assessment or collection of assessments (quizzes/tests)
  - Survey responses
  - Other predictive model outputs

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Thank You!

Questions?

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Paper: http://tiny.cc/**aied_communication_paper**

Code: http://github.com/**CAHLR/Communicator**

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