

Statistical Student Modeling

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Batch No. - 48

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- 1 Introduction
- 2 Literature Survey
 - Algorithm
 - Extensions
 - Alternatives
- 3 Requirements
 - Hardware
 - Software
- 4 Timeline
 - Back End
 - Front End

- **Domain:** Educational data mining, statistical learning

Problem Statement / Definition

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- **What:** An Intelligent Tutoring System (ITS)
- **How:** Several algorithms proposed in literature, based on BKT
- **Data:** 2009-10 Skill-builder ASSISTments data
- **Metrics:** RMSE, MAE

- Adaptive teaching systems for elucidating concepts

Intelligent Tutoring Systems

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- Generated interest after Corbett & Anderson, 1994.

- Model students learning state

Motivation

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- Use non-traditional cues, e.g. affect

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- Use non-traditional cues, e.g. affect
- Can modeling help improve education?

So what are we doing?

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- Individual models for each user

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- Implement a web-based ITS solution
- Individual models for each user
- Idea: start with simple models (single concept, basic BKT), go increasingly complex, hopefully implement KAT.

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Bayesian Knowledge Tracing (BKT)

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- Fundamentally, a two-state HMM—*learned* and *unlearned*.
- Viterbi algorithm can be used to solve for the hidden state sequence.

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- Pardos and Heffernan, 2011. Incorporated problem difficulty.
- Yudelson et al., 2013. Incorporated student learning speed.
- Schultz and Arroyo, 2014. Combined BKT with HMM-IRT, called Knowledge and Affect Tracing (KAT) model.
- Lin and Chi, 2016. Added student response time directly into the model, creating the Intervention-BKT (I-BKT).
- Spaulding, Gordon, Brezeal, 2016. Used commercial affect-analysis tool called Affdex.

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Why not Deep Neural Networks?

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- RNNs, LSTMs successfully applied (Piech et al., 2015; Lin and Chi, 2017)
- Difficult to interpret!
- With HMMs, can identify "most likely" hidden state sequence, and can also find HMM parameters (EM algorithm)

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- Working router
- Computer

- 2 GB RAM
- Optional: GPU, if using affect-aware models

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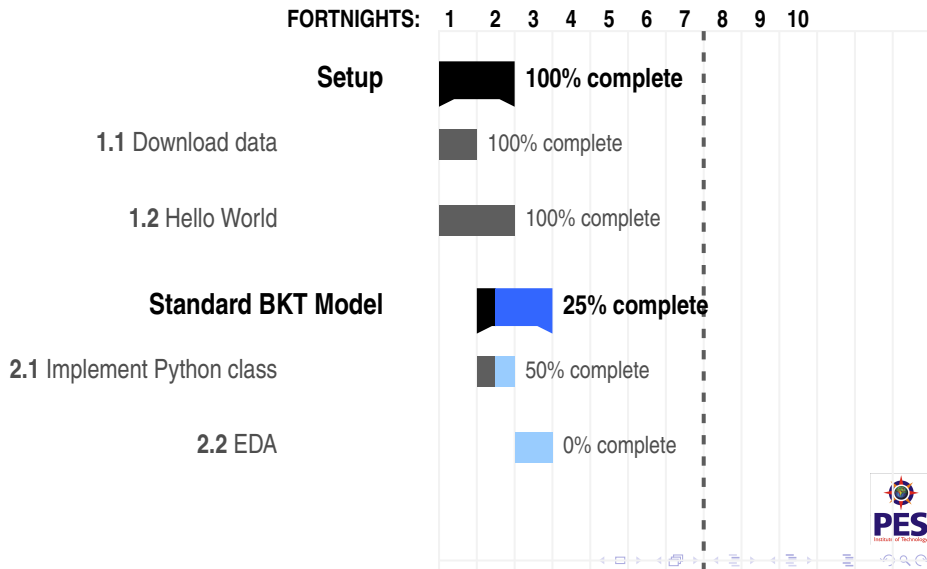
Recent web browser

- Python, Flask
- Node.js, npm
- pycodestyle
- GNU/Linux

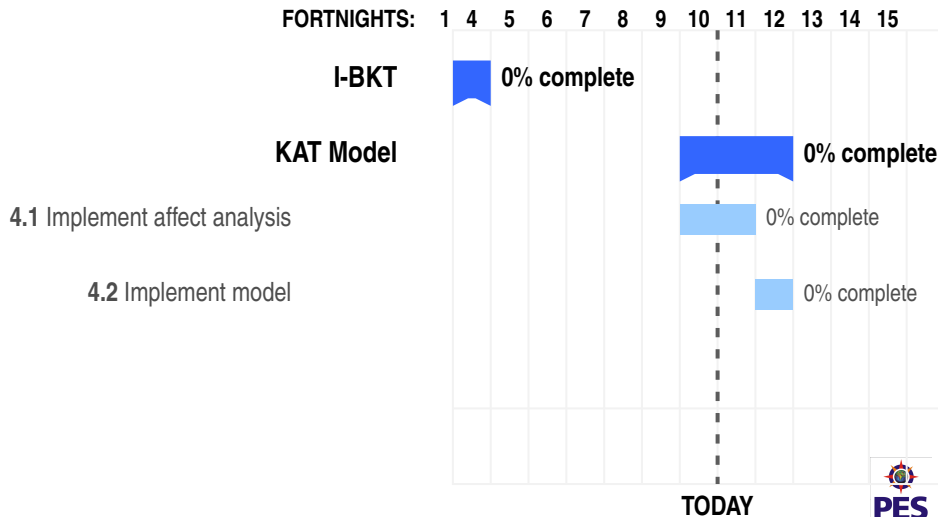
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Timeline from Sep 12 (first commit) to Oct 24 (F3)



Timeline from Oct 24, 2018 (F4) to April 10, 2019 (F15)



Timeline from [expand]

References



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The End