Statistical Student Modeling

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Ms. Kundhavai K R Batch No. - 48





Overview

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





• Domain: Educational data mining, statistical learning



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- What: An Intelligent Tutoring System (ITS)





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- How: Several algorithms proposed in literature, based on BKT





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- Domain: Educational data mining, statistical learning
- 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





Intelligent Tutoring Systems

Adaptive teaching systems for elucidating concepts





Intelligent Tutoring Systems

- Adaptive teaching systems for elucidating concepts
- Primarily based on Hidden Markov Models (HMMs)





Intelligent Tutoring Systems

- Adaptive teaching systems for elucidating concepts
- Primarily based on Hidden Markov Models (HMMs)
- Generated interest after Corbett & Anderson, 1994.





Motivation

Model students learning state





Motivation

- Model students learning state
- Use non-traditional cues, e.g. affect



5/26



Motivation

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





So what are we doing?

• Implement a web-based ITS solution



So what are we doing?

- Implement a web-based ITS solution
- Individual models for each user





So what are we doing?

- 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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Bayesian Knowledge Tracing (BKT)

- Proposed by Corbett & Anderson, 1994.
- Fundamentally, a two-state HMM-learned and unlearned.
- Viterbi algorithm can be used to solve for the hidden state sequence.





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BKT Extensions

- 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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 RNNs, LSTMs successfully applied (Piech et al., 2015; Lin and Chi, 2017)





Why not Deep Neural Networks?

- RNNs, LSTMs successfully applied (Piech et al., 2015; Lin and Chi, 2017)
- Difficult to interpret!





Why not Deep Neural Networks?

- 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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User

- Working router
- Computer





Server

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





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User

Recent web browser



Server

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





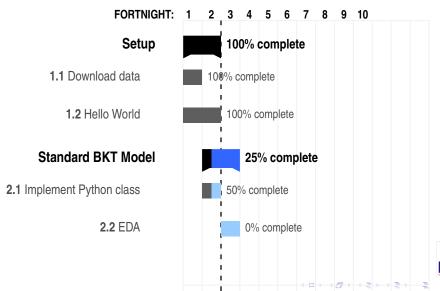
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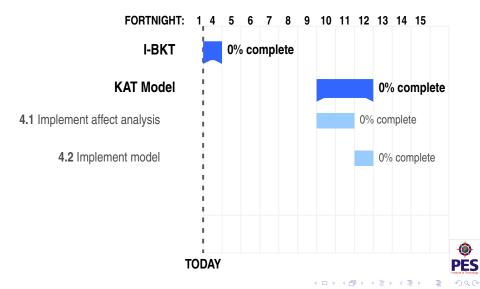


Timeline from Sep 12 (first commit) to Oct 24 (F3)





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



Timeline from [expand]



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The End



