Statistical Student Modeling

Rahul Yedida
Ankush Kumar
Srihari Joshi
Vima Rai

Ms. Kundhavai K R
Batch No. - 48

October 9, 2018

Overview

Problem Statement / Definition

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

Problem Statement / Definition

- **Domain:** Educational data mining, statistical learning
- **What:** An Intelligent Tutoring System (ITS)

Problem Statement / Definition

- **Domain:** Educational data mining, statistical learning
- **What:** An Intelligent Tutoring System (ITS)
- **How:** Several algorithms proposed in literature, based on BKT

Problem Statement / Definition

- **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

Problem Statement / Definition

- **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

PES Institute of Technology

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

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.

Overview

Bayesian Knowledge Tracing (BKT)

- Proposed by Corbett & Anderson, 1994.

Bayesian Knowledge Tracing (BKT)

- Proposed by Corbett & Anderson, 1994.
- Fundamentally, a two-state HMM–*learned* and *unlearned*.

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.

Overview

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.

Overview

Why not Deep Neural Networks?

- 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)

Overview

User

- Working router
- Computer

Server

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

Overview

User

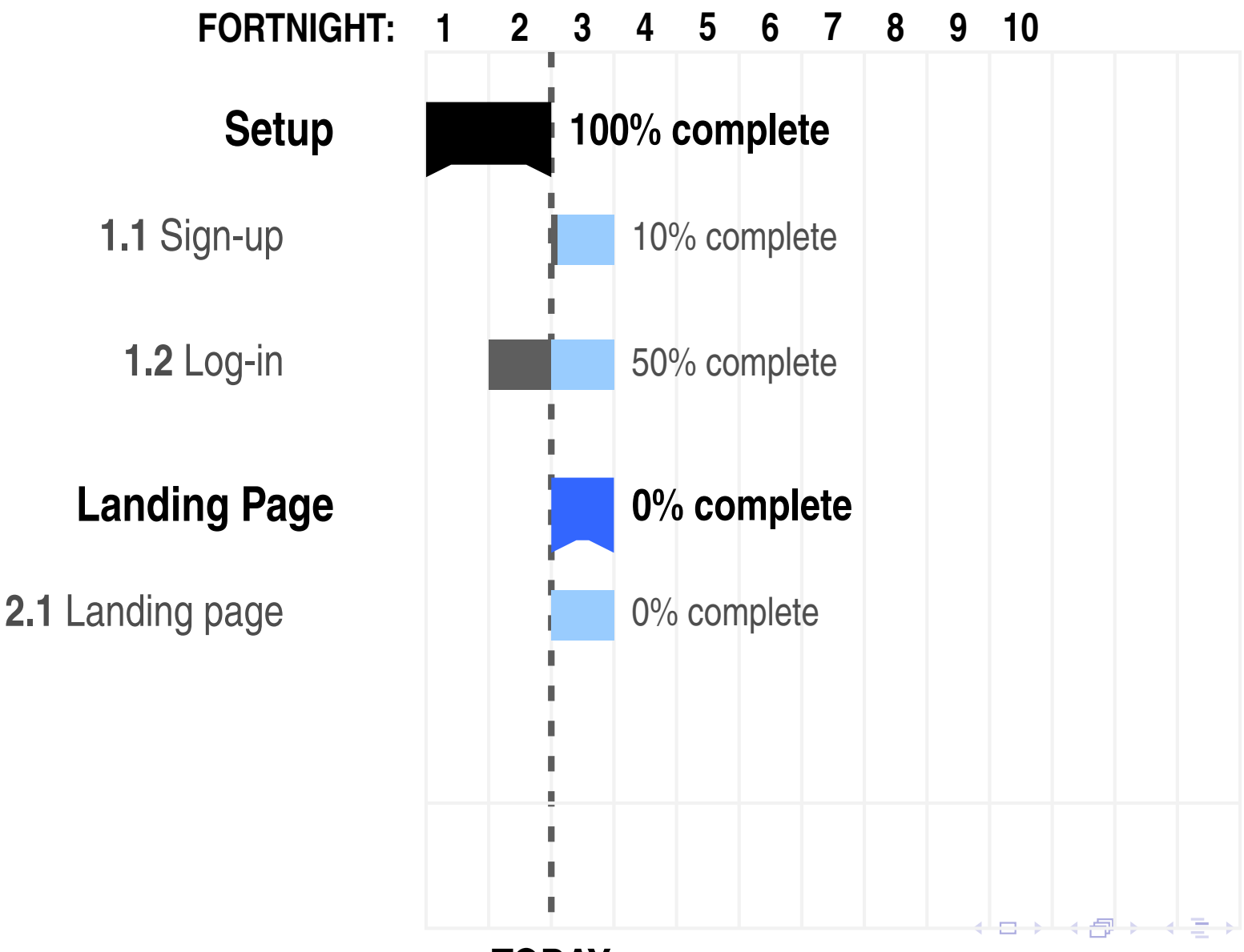
Recent web browser

Server

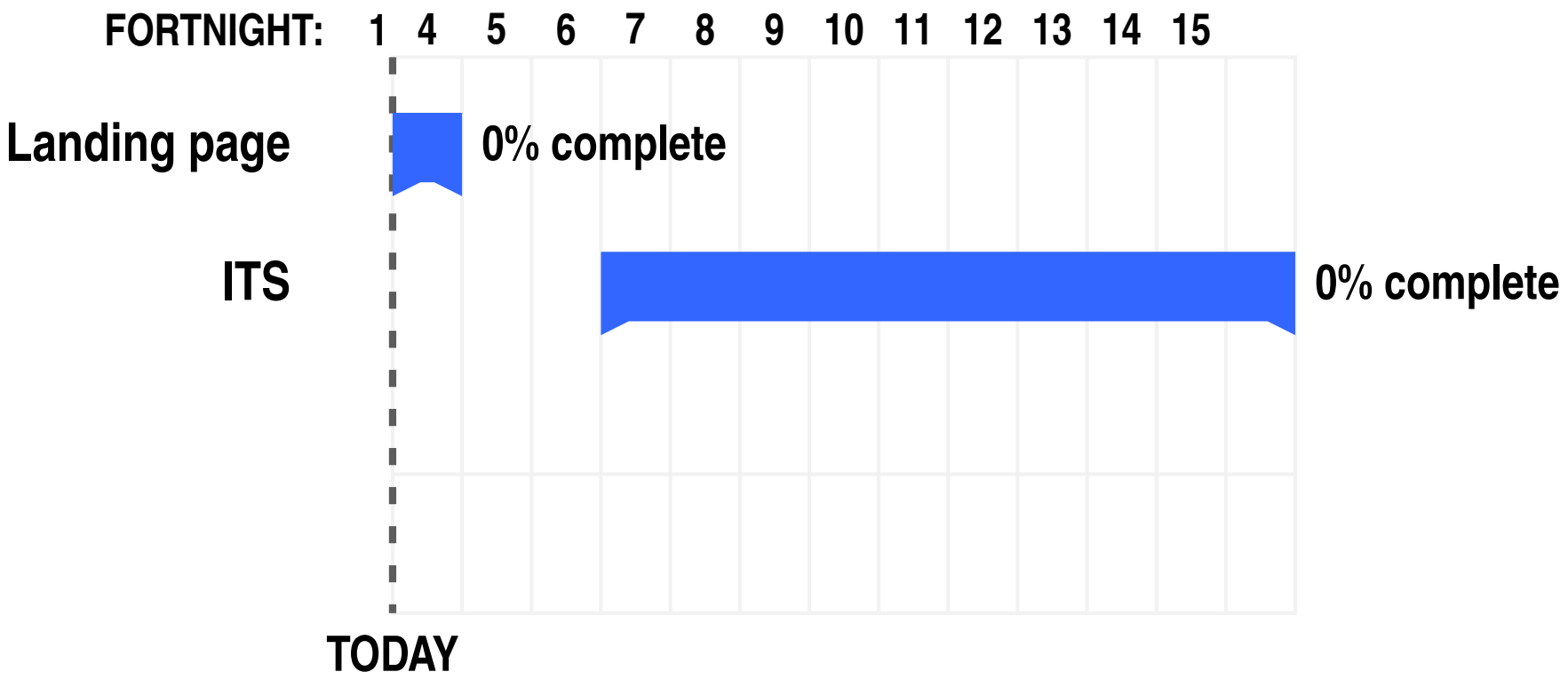
- Python, Flask
- Node.js, npm
- pycodestyle
- GNU/Linux

Overview

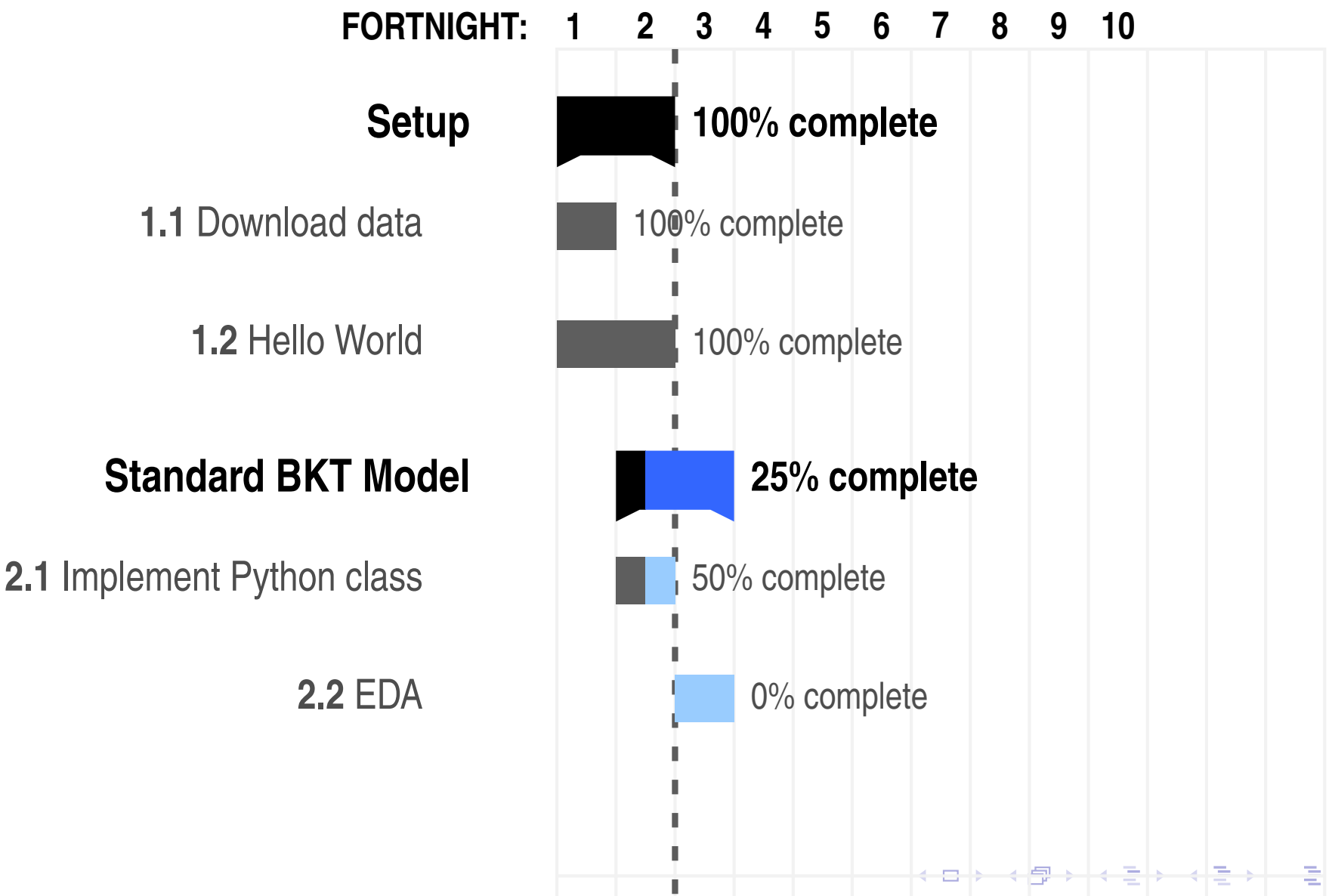
Timeline from Sep 12 (first commit) to Oct 24 (F3)



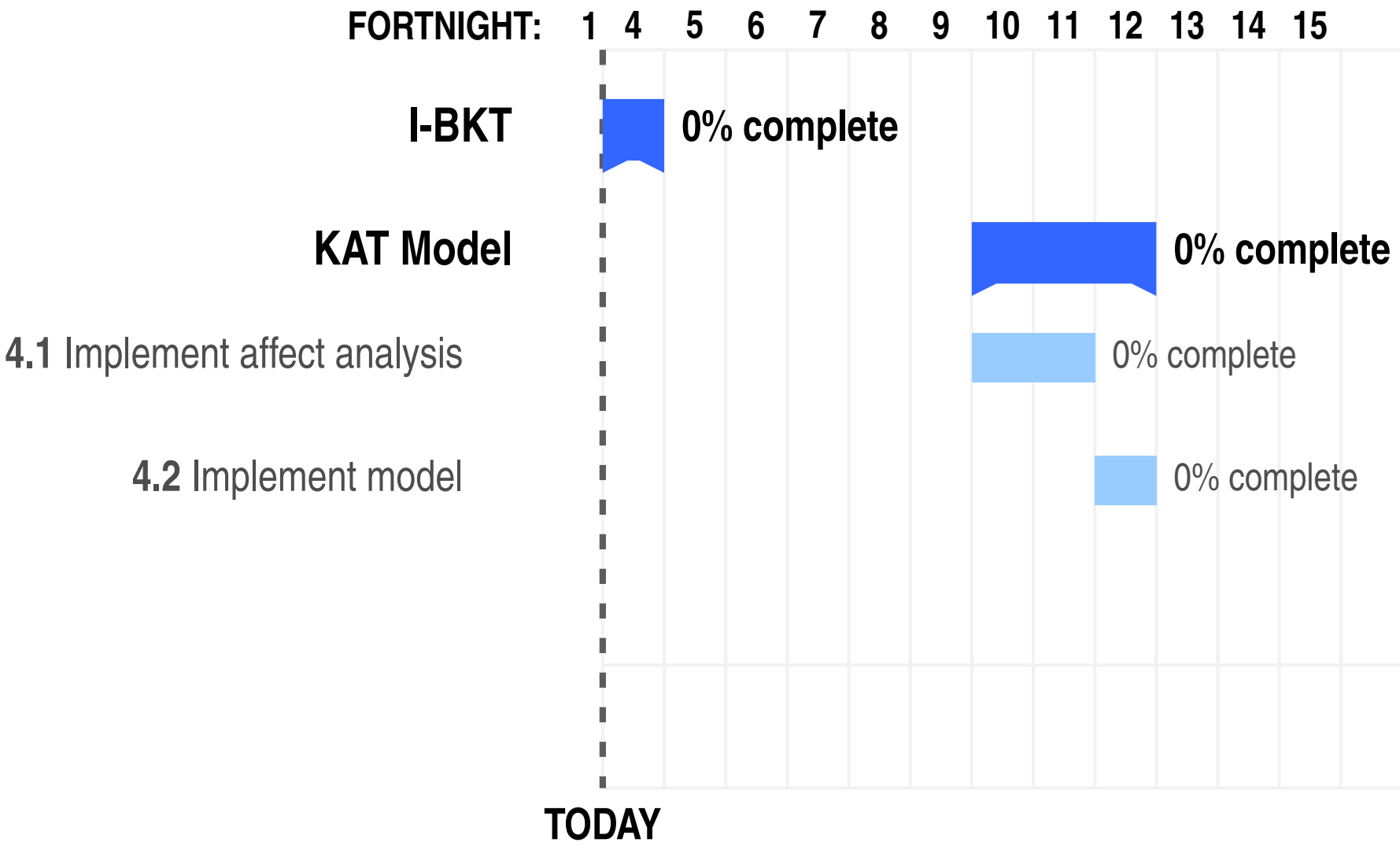
Timeline from Oct 24, 2018 (F4) to April 10, 2019 (F15)



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



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



References

A. T. Corbett and J. R. Anderson (1994)

Knowledge tracing: Modeling the acquisition of procedural knowledge

User modeling and user-adapted interaction, 4(4), 253 – 278.

R. S. d Baker, A. T. Corbett, and V. Aleven (2008)

More accurate student modeling through contextual estimation of slip and guess probabilities in bayesian knowledge tracing

Intelligent Tutoring Systems, 253 – 278, Springer.

C. Lin and M. Chi (2016)

Intervention-bkt: incorporating instructional interventions into bayesian knowledge tracing

International Conference on Intelligent Tutoring Systems, 208 – 218, Springer.

S. Chiappa and S. Bengio (2003)

Hmm and iohmm modeling of eeg rhythms for asynchronous bci systems

Tech. rep., IDIAP.

References

S. Spaulding, G. Gordon, and C. Breazeal (2016)

Affect-aware student models for robot tutors

Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems, 864 – 872, International Foundation for Autonomous Agents and Multiagent Systems.

S. Schultz and I. Arroyo (2014)

Tracing knowledge and engagement in parallel in an intelligent tutoring system

Educational Data Mining.

Z. A. Pardos and N. T. Heffernan (2011)

Kt-idem: introducing item difficulty to the knowledge tracing model

International Conference on User Modeling, Adaptation, and Personalization, 243 – 254, Springer.

M. V. Yudelson, K. R. Koedinger, and G. J. Gordon (2013)

Individualized bayesian knowledge tracing models

International Conference on Artificial Intelligence in Education, 171 – 180, Springer.

References

C. Piech, J. Bassen, J. Huang, S. Ganguli, M. Sahami, L. J. Guibas, and J. Sohl-Dickstein, (2015)

Deep knowledge tracing

Advances in Neural Information Processing Systems, 505 – 513.

C. Lin and M. Chi (2017)

A comparisons of bkt, rnn and lstm for learning gain prediction

International Conference on Artificial Intelligence in Education, 536 – 539, Springer.

Z. C. Lipton, D. C. Kale, C. Elkan, and R. Wetzel (2015)

Learning to diagnose with lstm recurrent neural networks

arXiv preprint, arXiv:1511.03677.

J. Johns and B. Woolf (2006)

A dynamic mixture model to detect student motivation and proficiency

Proceedings of the National Conference on Artificial Intelligence, 21(1), 163, AAAI Press; MIT Press.

The End