Statistical Student Modeling

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Overview

Problem Statement / Definition

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- **Data:** 2009-10 Skill-builder ASSISTments data
- **Metrics:** RMSE, MAE

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- Generated interest after Corbett & Anderson, 1994.

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

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- Idea: start with simple models (single concept, basic BKT), go increasingly complex, hopefully implement KAT.

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- 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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- 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

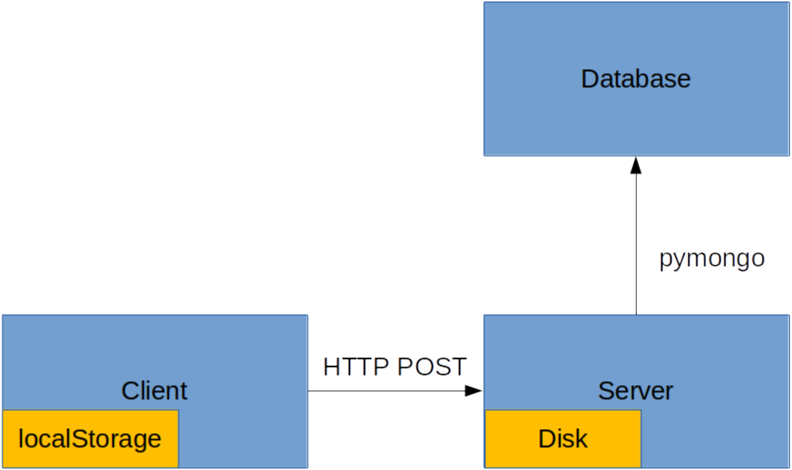
Server

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

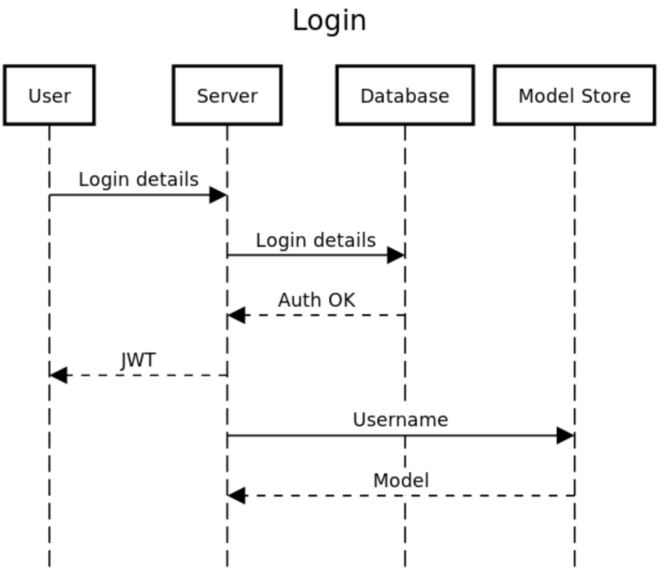
We

Overview

High level design



Sequence diagram



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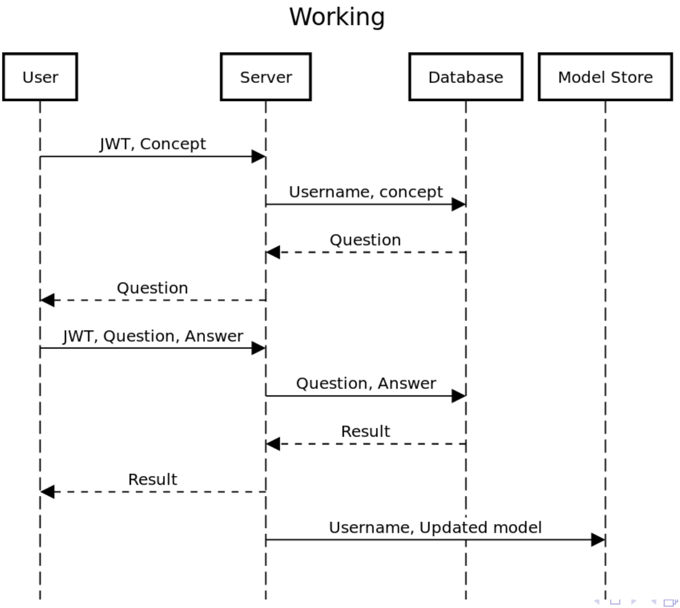
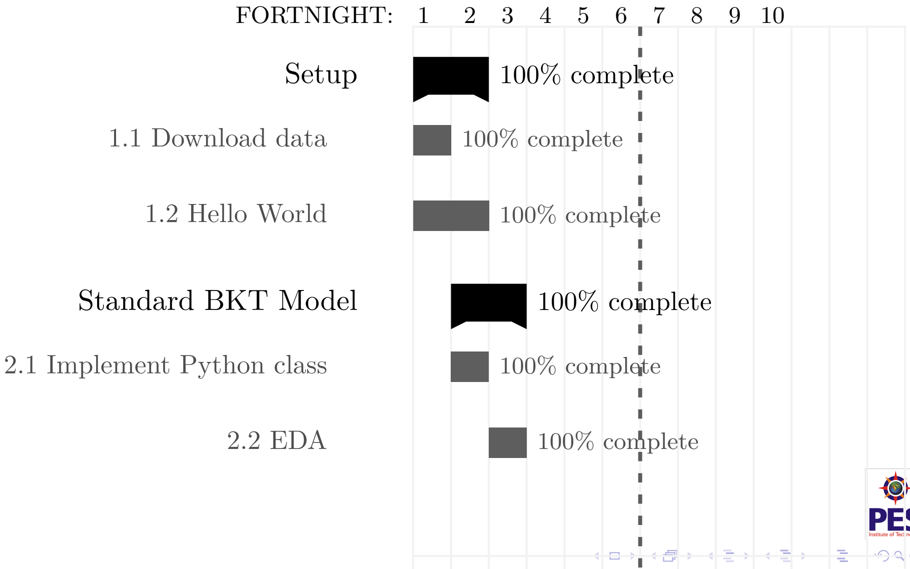
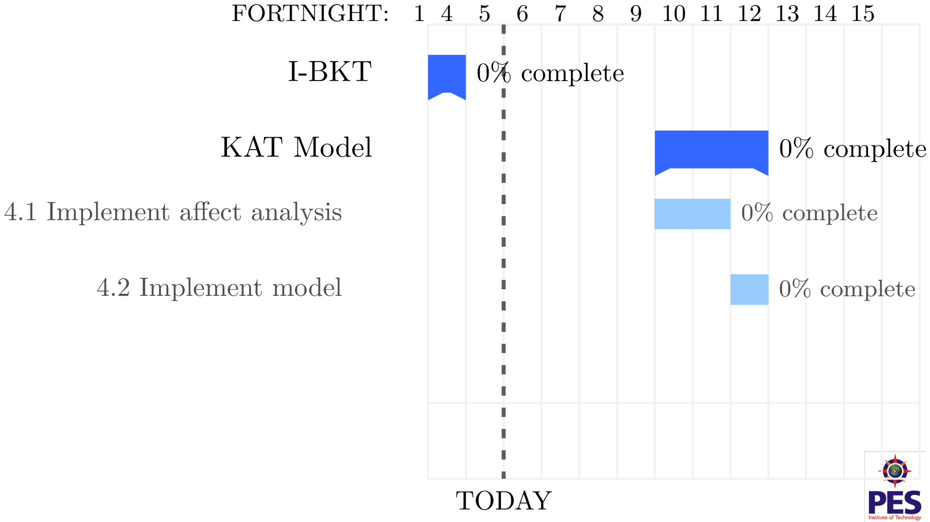


Overview

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



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



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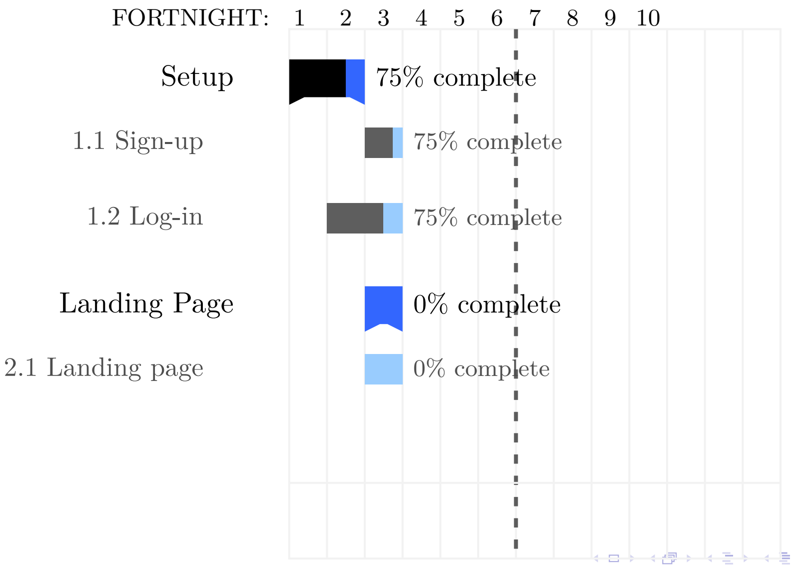

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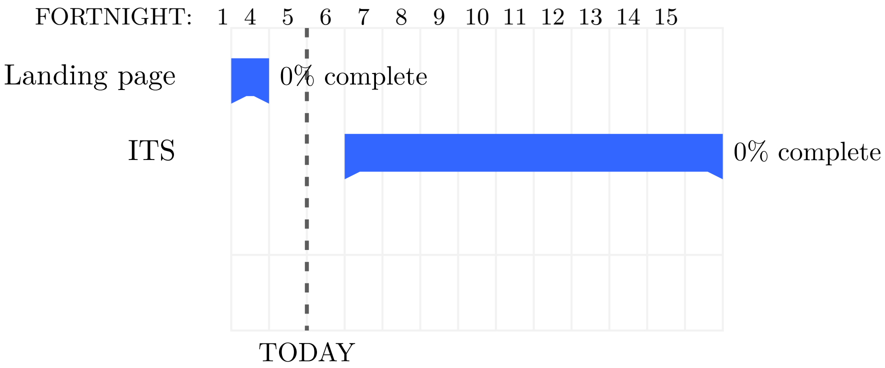

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