Reproduction of Predicting E-Learning Student's Performance

Alsulami et al. 2023

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An Overview:

Where we're going

1. Background
2. Methods
3. What I aimed to reproduce
4. Results
5. Discussion

Background

- Original paper (**Alsulami et al. 2023**) looked at methods to predict E-Learner student performance
  - Diversity in modality of instruction and learning can provide more accessibility, and lend itself to more equitable education opportunities.
  - Ever increasing amount of data generated especially with the increase of online learning post COVID
  - How can we leverage that data to improve our education systems?

--> Alsulami et al. 2023: explores how to predict student performance by combining **machine learning,** where computer models learn patterns from data to make predictions, with **ensemble methods,** where multiple computer models work together to predict.

  - **Machine learning (ML)**: computers learn how to make predictions themselves ("Here's what student success looks like— figure out how to predict it")
  - **Ensemble methods**: several computer models work together and share their answers to make a prediction (combining their strengths usually leads to a more accurate result)

Methodology

Data; Training and Testing

- **Data:** obtained from the Kalboard 360 E-Learning system via the Experience API (XAPI).
  - 480 students with 17 attributes (demographic, academic, and behavioral)

- Split it into training and testing data
  - **K-fold cross-validation:** Divide data into 10 equal parts (folds). 9 of these folds are used to train the model, the remaining fold is used to test it.
  - Process is repeated for each fold, and the average accuracy from all tests is taken.
  - The entire procedure was repeated 10 times for each model

Methodology

The ML Models and Ensemble Methods

ML Models

- **Decision Trees (DT)**
- **Random Forests (RF)**
- **Naive Bayes (NB)**

Ensemble Techniques

- **Boosting**
- **Bagging**
- **Voting**

dataset → **ML Models (alone)**
DT
NB
RF

→ **Boosting Added**
DF
NB
RF
DT + NB*
RF + DT*
NB + RF + DT*

→ **Bagging Added**
DF
NB
RF
DT + NB*
RF + DT*
NB + RF + DT*

→ **model evaluation**

***voting used as well**

What I wanted to reproduce:

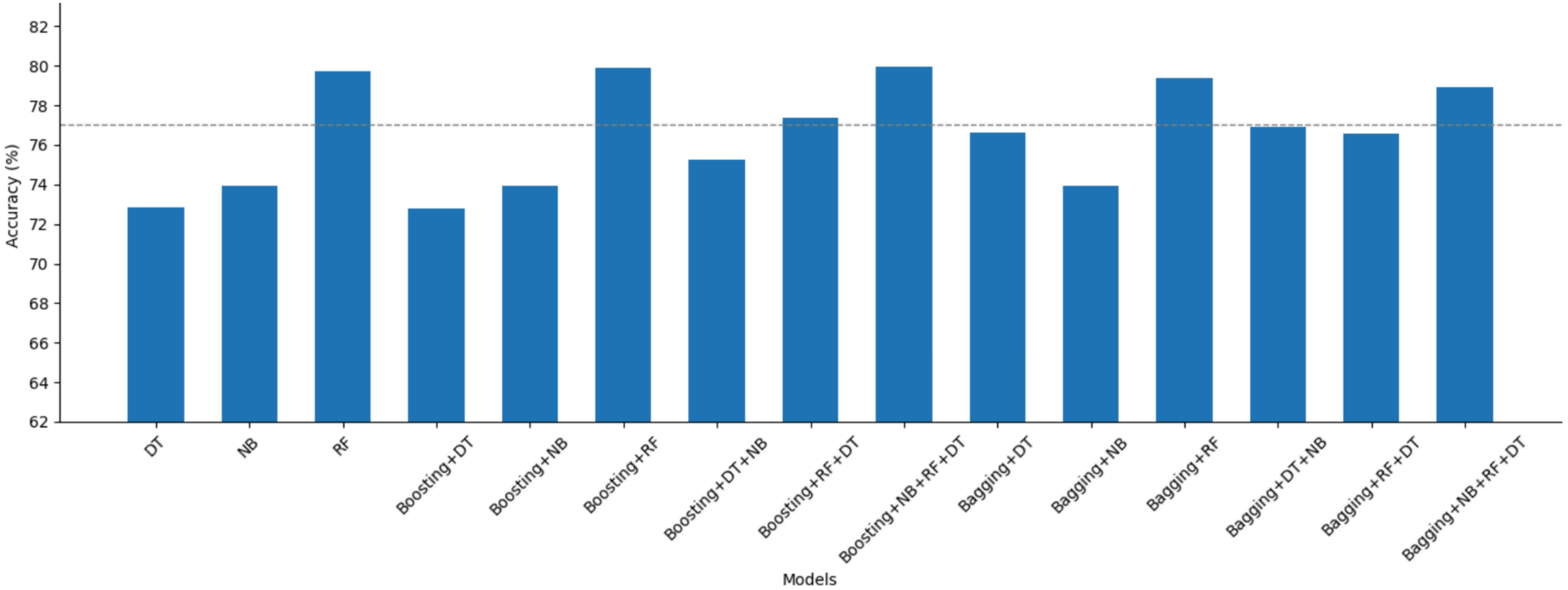
Accuracy

- With 15 experiments in total, how does one determine which one is the best at predicting student performance?
- **Accuracy**
  - metric used to evaluate the performance of a model
  - $\text{accuracy} = \frac{\text{\# correct predictions}}{\text{total \# of predictions}} \times 100$
  - In general: the higher the accuracy, the better!

- **Decision Trees with Boosting yielded the highest accuracy (77%) out of all models run**

Results

- Plotting accuracies for all 15 models



- y = 77: represents the DT + boosting result from authors
- Boosting + DT + NB + RF had the highest accuracy (79.98%)

Discussion

- Failed to reproduce
- Boosting + DT + NB + RF had the highest accuracy (79.98%)
    - Anticipated getting a slightly different accuracy, but I did not anticipate getting an entirely different model
- All models had accuracy above 72% (compared to their 65%)
- Explore different ML models and ensemble methods