

# Report Factors Influencing Learning and Predicting Academic Performance

M4 - Calcularis Crusaders

## 1 INTRODUCTION

Learning is a complex process that is influenced by many factors, including cognitive ability, motivation, and environmental factors. Understanding these factors can help educators design effective learning experiences and help students achieve better academic outcomes. In this report, we will discuss some key findings related to learning, failure, and forecasting scholastic achievement that we discovered while working for this milestone.

## 2 RESEARCH

### Factors Influencing Learning

Recent research has shown that effortful learning usually signals not only deeper learning but also more durable, long-lasting knowledge. These findings suggest that educators should design learning experiences that are challenging and require effortful learning to promote deep and durable learning outcomes.

### Learning from Failure

Failure can be a valuable learning experience. Good failures produced through experimentation at the frontier can help individuals learn quickly. Thus, it is essential to create an environment where failures are accepted and embraced as opportunities to learn and grow.

## 3 PREPROCESSING

Our preprocessing is based on the Calcularis skill map. We use information about games and skill levels to calculate mastery level. The data frame contains information about users, the games they played, and the difficulty level of the subtasks. This helps us classify subtasks and find corresponding records in the skill map. We also consider which games users played before and how they may influence task performance. We store mastery levels and user progress over weeks in a newly created data frame.

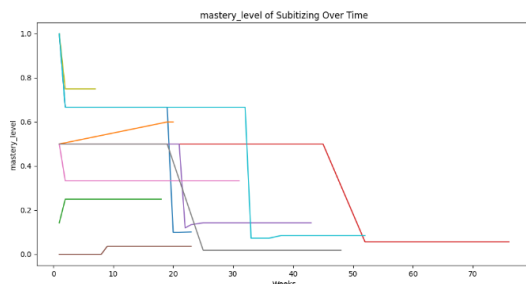


Fig. 1: Mastery level graph

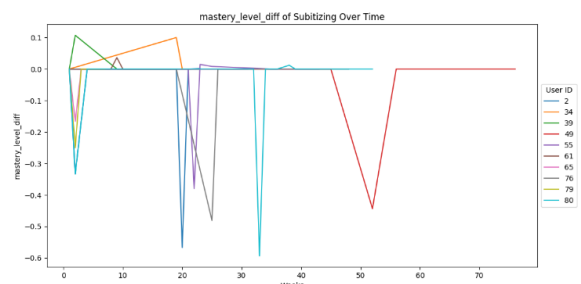


Fig. 2: Mastery level differences graph

## 4 MODELLING

Knowledge tracing is a way to model student knowledge over time. The task is to predict the student's future performance so that educators can create early interventions when a student's behaviour is not leading towards success. State-of-the-art models simply predict answer correctness based on a student's historical performance. Simple models that perform well are gradient-boosted decision forests, like LGBM. The current top performers on knowledge tracing competitions are transformer-based models that require lots of training data (Riiid Answer Correctness Prediction, 2021).

Research indicates that machine learning models outperform the simpler performance factors analysis (PFA) (Riiid Answer Correctness Prediction, 2021). Deep Knowledge tracing is the latest advancement in the area and uses a mechanism to store the state of the student's knowledge (memory, forgetfulness) and attention mechanisms to weigh certain behaviours more than others in order to make predictions about their future (Yu et

al., 2022). Features that track student performance over time help with predicting their future success. We added a cumulative percentage correct feature to track each student's average correctness for each skill.

## 5 EXPLAINABILITY

Decision tree based models have the benefit that you can view which factors lead to certain predictions using explainability tools. We also explored using SHAP explainability to see which factors most influence correctness and mastery. We also tried one-hot encoding the categorical features for a more fine-grained explainability but the effects were so small that there weren't noticeable differences between game\_name or number\_range categories. These plots show the difference between the model's feature importance and SHAP's feature impacts.

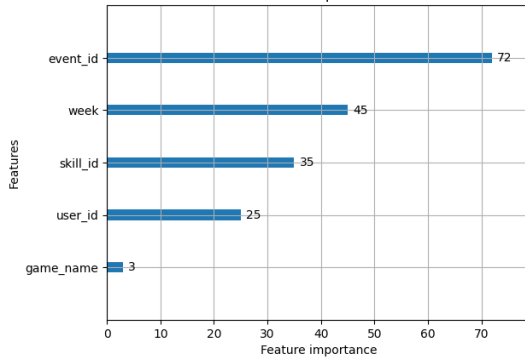


Fig. 3: Feature importance

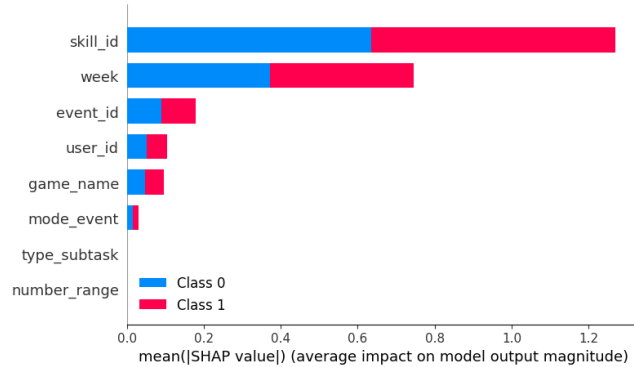


Fig. 4: SHAP explainability summary

We can also break down the SHAP feature impact per value. For example, we can see that some skills influence mastery levels positively and some negatively.

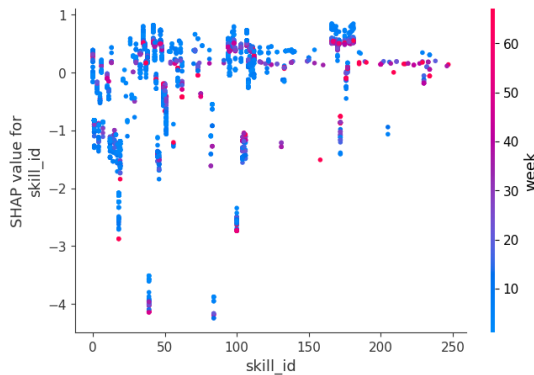


Fig. 5: SHAP dependence plot

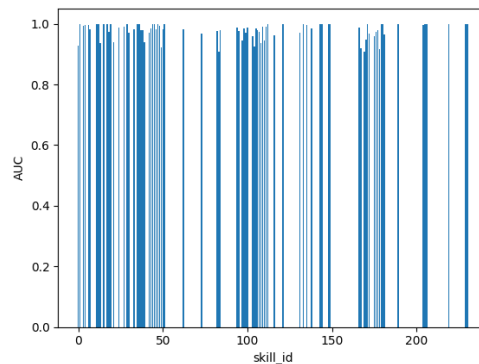


Fig. 6: AUC per skill id for LGBM

## 6 EVALUATION

We compare our models to a baseline to see if they perform better. We also check if certain skills are easier to model than others by plotting their individual AUCs. The model that uses a cumulative percent correct feature performs better than one without as we can see in fig.6 above.

## 7 CONCLUSION

Learning is a complex process that is influenced by many factors, including cognitive ability, motivation, and environmental factors. Effortful learning promotes deep and durable knowledge, and failure can be a valuable learning experience. Predictive models have been developed to identify students at risk of failing based on factors such as system access and navigational actions. These models can help educators intervene early and provide students with targeted support to improve their academic outcomes.

## REFERENCES

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