Maximizing OU Student Success by Predicting Student Failure

CS773 Capstone project

Alex Launi
Old Dominion University
01124306

Summer 2019

Contents

List of Figures

1 Executive Summary

The objective of this project is to develop models that can predict student success within a course module so that educators can intervene at the earliest indications of trouble, to help prevent said student from failing, or withdrawing from the course.
Two types of data are used to achieve this goal.

- Student demographic data
- Student-VLE interaction data

2 Introduction

Education is of prime importance for economic mobility. Broadband internet has made it possible for quality educational products to be made available to a much wider swath of the population. Traditionally, at least in the United States, educational resources were not distributed equally to all individuals. Numerous studies have shown the correlation between zip code, economic mobility, and quality of education. The possibility of delivering high quality education products to students in disparate areas is very exciting. In order to maximize the potential gain this system has to offer I have developed predictive models that will enable administrators, educators, and mentors the ability to identify students who are at an elevated risk of not completing their module so that an intervention may be conducted and the student guided back to success.

The Open University (OU) is open to students regardless of previous educational history, and offers hundreds of distance learning courses. The virtual learning environment is the portal through which OU students interact with the course materials, much in the way that Blackboard and PLE function for ODU online students. Students are grouped into small class sizes and a teaching assistant is assigned to provide help, grade assignments, and guide the cohort through the course.

A reliable means to identify at-risk students before too much damage is done would be a major boon the success of the program as a whole. An online program could potentially have many more students than traditional classroom based programs. The cost of too many interventions could be prohibitively high, and many may be false positives; worse there may be many false negatives.

3 Problem Statement

Our goal is to identify students who need some form of intervention so that teaching assistants, and OU administration can best target intervention to the students for whom it will have the most impact. To achieve this goal we attempt to utilize student demographics, course interaction data, and student performance data for students in the same course.

4 Methodology

This project used the anonymized Open University Learning Analytics Dataset (OULAD). The data was collected by the Open University to help optimize learning materials. It is comprised of student demographics, assessment results, and click-stream data for over 32,000 students across 22 courses. 1,111 entries had missing values of imd_band. Instances with missing data were removed from the dataset. 3,516 entries with imd_band "10-20" were relabelled "10-20%" for consistency. The criterion for `at risk` was considered in 2 distinct groups and the experiments were run independently to see if failure and drop out could be treated as one, or if they were distinct variants of students in need of help. For each model Stratified 5-fold cross validation was performed. Models were evaluated based on F-measure, precision, recall, and accuracy. Scores reported are the mean of the 5 runs.

4.1 Learning Models

In this project 4 machine learning models were employed. Decision Tree classification, Logistic Regression classification, Random Forest, and Support Vector Machines. All models were implemented in Python using models from the scikit-learn library both for preprocessing, and learning. Feature engineering was performed both by intuition gained from exploratory data analysis, and with scikit-learn's recursive feature elimination. No significant difference in predictive ability of the models was observed between these two methods, validating the conclusions reached during data analysis.

4.1.1 Decision Tree Classification

Decision tree classification was performed with the `sklearn.trees.DecisionTree` class. No hyperparameter optimization was performed with the exception of `max_depth` hyperparameter which was set to `max_depth = 3` in order to reduce the tree to a size conducive to printing for visualization purposes. Splits were performed based on feature entropy.

4.1.2 Random Forest

Random forest was performed in an indentical fashion to the decision tree model with the exception that sklearn's RFE class was used in lieu of features selected during EDA.

4.1.3 Logistic Regression

Logistic regression was performed both on demographic data, and VLE interaction data. Feature scaling was attempted, but no change in prediction power was observed.

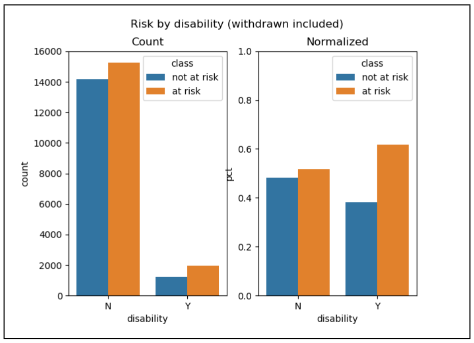
4.1.4 SVM

SVM using the radial basis function kernel was performed on VLE interaction data and results compared to logistic regression.

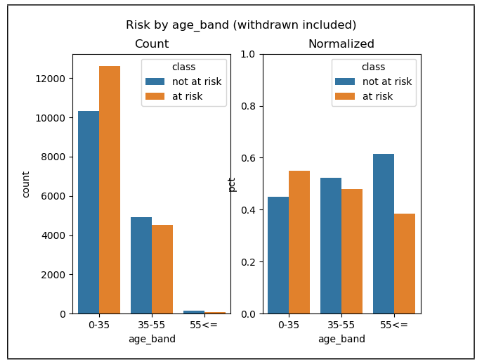
4.2 Failure and Withdrawn `at risk`

The data were evaluated for any obvious connection between feature and risk, both as raw counts and as normalized values. This analysis yielded disability, education level, and region as potentially strong demographic indicators of risk. Relationship between feature and risk for data with withdrawn students is shown as raw count, and in normalized form in Figure 1.

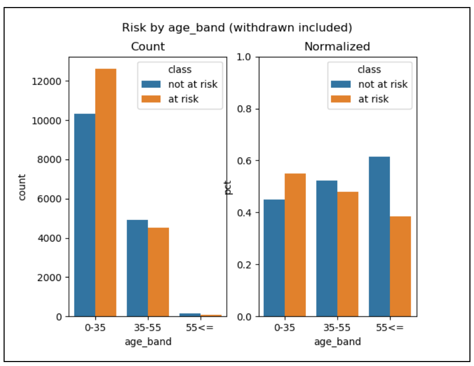
Student activity was evaluated as a predictor of success. The activity level of students who passed courses showed a much narrower range per day. Students who failed or withdrew displayed lower amounts of activity, until the last portion of their courses where they exhibited a dramatic spike in activity, likely as an attempt to make up lost time (shown in Figure 2).



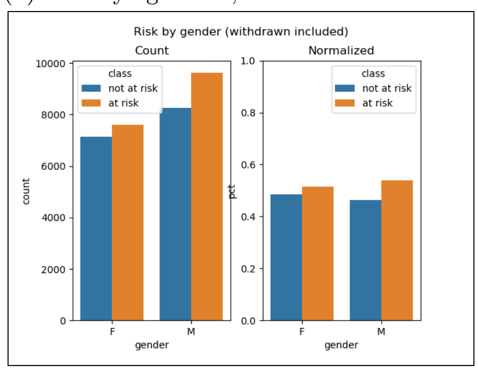
(a) Risk by disability, count and normalized



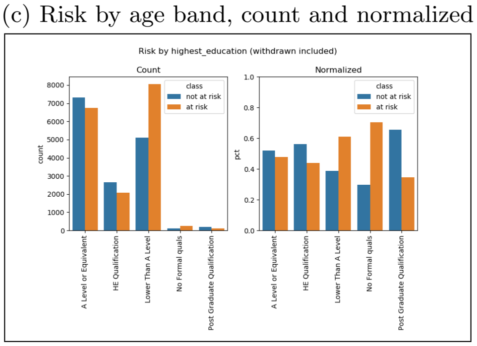
(b) Risk by age band, count and normalized



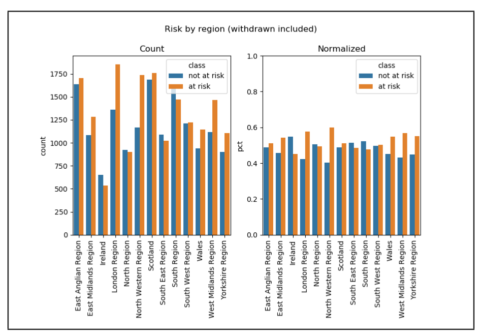
(c) Risk by age band, count and normalized



(d) Risk by gender, count and normalized



(e) Risk by highest education level, count and normalized



(f) Risk by region, count and normalized

Figure 1: Risk by feature for all `at risk` students

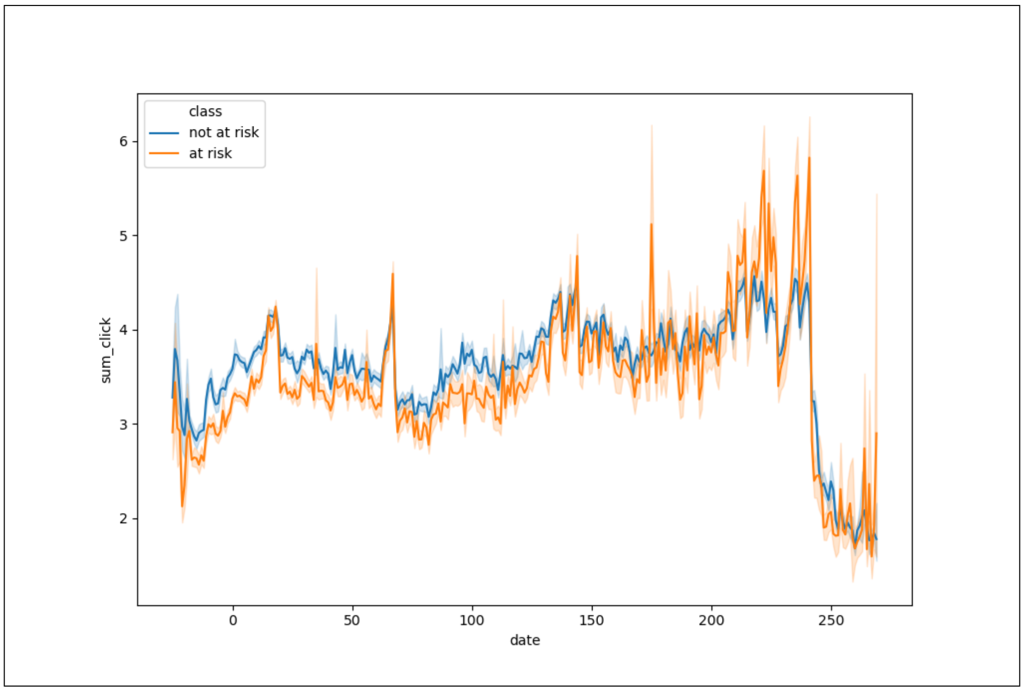
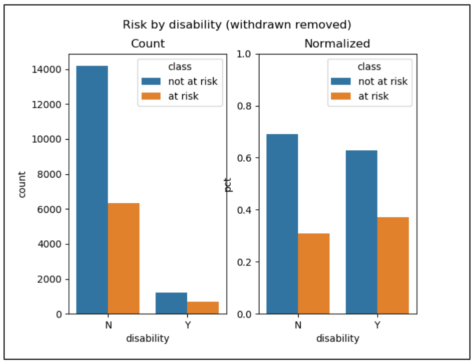
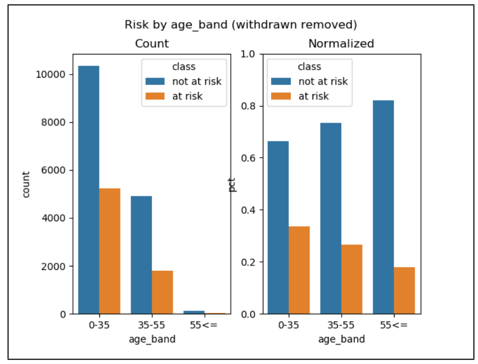


Figure 2: Mean clicks per day (withdrawn at risk)

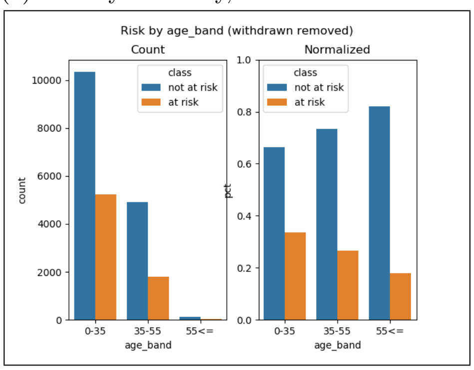
4.3 Only failure `at risk`



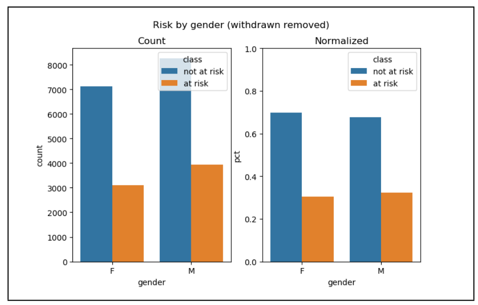
(a) Risk by disability, count and normalized



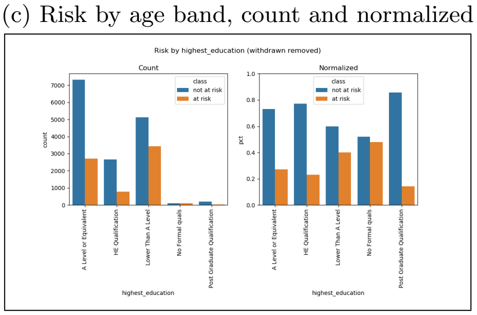
(b) Risk by age band, count and normalized



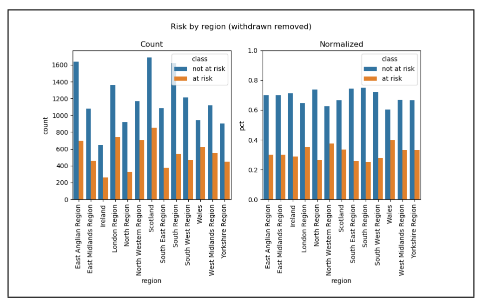
(c) Risk by age band, count and normalized



(d) Risk by gender, count and normalized



(e) Risk by highest education level, count and normalized



(f) Risk by region, count and normalized

Figure 3: Risk by feature for failure only data

After removing students who had withdrawn the dataset become unbalanced with 32% `at risk` and 68% `not at risk`. Additionally, the apparent connection between features and risk changed. Age became a much stronger predictor, disability fell, region and highest education achieved remained strong indicators, however. This relationship is shown in Figure 3

Student activity exhibited an almost identical pattern with withdrawn students removed from the dataset (Figure 4). This bore itself out during the experiments, and is discussed further in the conclusion.

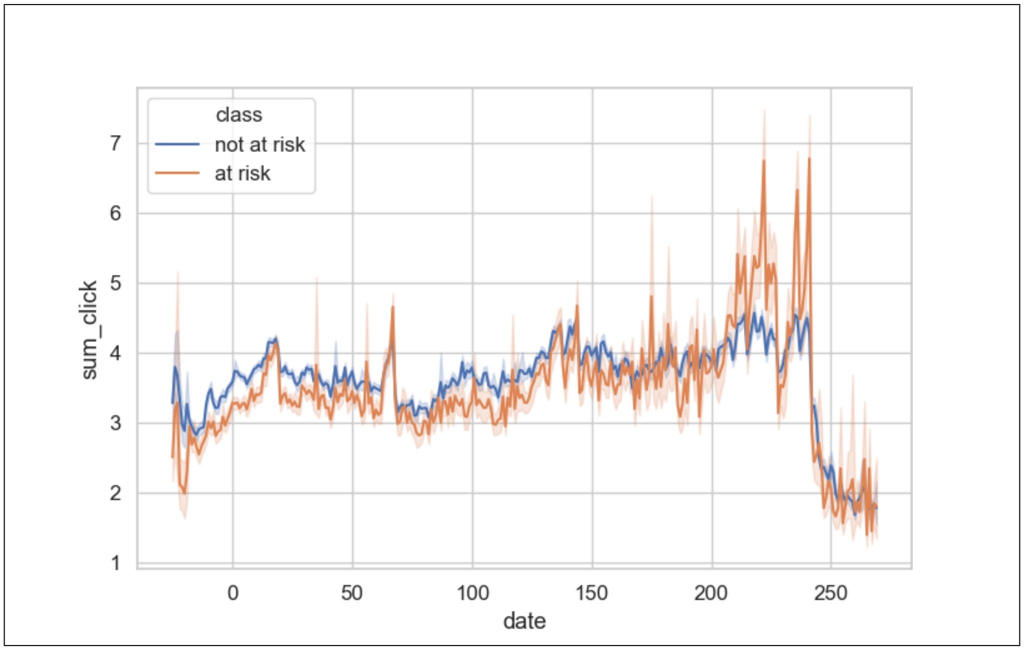


Figure 4: Mean clicks per day (withdrawn removed)

5 Experimental Setup and Data

The data consists of 7 .csv files forming a database connecting student demographics, course data, assessment data, and VLE interaction click-stream data as shown in Figure 5. The problem will be modeled as a binary classification problem consisting of two classes: `at risk`, and `not at risk`. `studentinfo.csv` classifies students as `Distinction, Pass, Fail, Withdawn`. In all cases I have consolidated `pass`, and `distinction` into the single classification of `not at risk`. What consitutes risk however is not as straight forward. I have chosen to analyze the data in 2 ways:

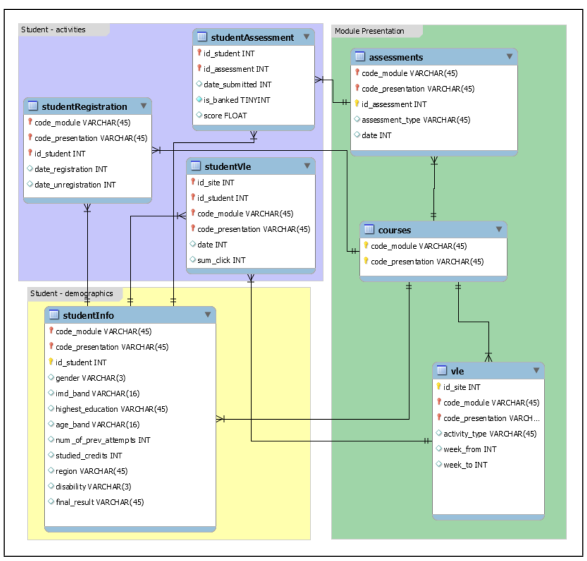


Figure 5: OULAD database schema

- Withdrawn and failure → `at risk`

- Withdrawn removed; only failure → `at risk`

5.1 Failure and Withdrawn `at risk`

`studentinfo.csv` contains 32,593 instances with students who have withdrawn included. Of these 17,208 (53%) are `at risk`, and 15,385 (47%) are `not at risk`.

5.1.1 Demographics

A model was trained first with all features, and then recursive feature elimination was used.

Decision Tree, all features, no pruning	F1:	0.5300751596360103
	P:	0.55853345228728
	R:	0.5122745504163213
	ACC:	0.5213455954803108
Decision Tree, all features, pruned to depth = 3	F1:	0.5960770313754884
	P:	0.6084919709282606
	R:	0.6010087413775903
	ACC:	0.577632558938233
Logistic regression, all features	F1:	0.6033966349724211
	P:	0.6002020723205602
	R:	0.6521749970644297
	ACC:	0.5698497943495411
Random Forest, all features	F1:	0.5885641454642756
	P:	0.5789355549279234
	R:	0.612470072634394
	ACC:	0.5513946255038854
Random Forest, all features, pruned to depth = 3	**F1**:	**0.666812465970329**
	P:	0.5723193485418702
	R:	0.8068065322396238
	ACC:	**0.5721045993342264**
Decision Tree, highest_education, region, gender, disability, no pruning	F1:	0.6194940570468739
	P:	0.589318894225182
	R:	0.6582959743400265
	ACC:	0.5701985667526074
Decision Tree, highest_education, region, gender, disability, pruned to depth = 3. *Illustrated in Figure 6*	F1:	0.5917318113490284
	P:	0.5983365588565791
	R:	0.594766915726622
	ACC:	0.5652109402855962
Logistic regression, highest_education, region, gender, disability, no pruning	F1:	0.5930103011463939
	P:	0.5806063792573536
	R:	0.6162824292218575
	ACC:	0.5549203559751633
Random Forest, highest_education, region, gender, disability, no pruning	F1:	0.6253177280985549
	P:	0.587579935347121
	R:	0.6793333033154727
	ACC:	0.5721054064792355
Random Forest, highest_education, region, gender, disability, pruned to depth = 3	**F1**:	**0.6579396580825498**
	P:	0.5673330923414592
	R:	0.7921906240095209
	ACC:	**0.5628288434883273**

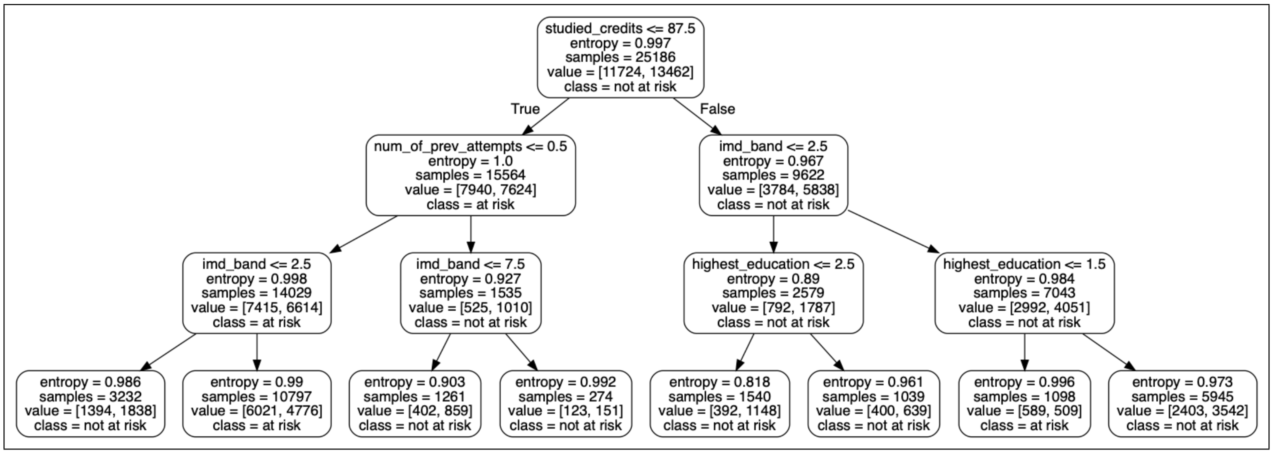


Figure 6: Demographic based decision tree classifier (withdrawn at risk)

5.1.2 VLE Interaction

Logistic Regression, clicks per day	F1:	0.7851064207596459
	P:	0.7206436088430447
	R:	0.862602495543672
	ACC:	0.7690144139280324
SVM, mean clicks per day	F1:	0.8415578470397914
	P:	0.8992202025711
	R:	0.7911586452762924
	ACC:	0.8544488198550825
Logistic Regression, binary activity per day	F1	: 0.8302630656926905
	P:	0.8076095227708657
	R:	0.8546880570409983
	ACC:	0.8291667001054233
SVM, binary activity per day	**F1**:	**0.8561210723707424**
	P:	0.9334441815817172
	R:	0.7910873440285205
	ACC:	**0.8701753893183237**

5.2 Only failure `at risk`

It is reasonable that students who withdraw and students who fail face different stressors, and their demographics and behaviors may not align. By removing students who withdraw and treating just those that fail separately I attempt to show that we can increase classification performance. `studentinfo.csv` contains 21,562 instances with students who have withdrawn included. Of these 6907 (32%) are `at risk`, and 14,655 (68%) are `not at risk`.

5.2.1 Demographics

Decision Tree, all features, no pruning	F1:	0.3551014504455618
	P:	0.34250211116095125
	R:	0.4012139109330578
	ACC:	0.5507328880585811
Decision Tree, all features, pruned to depth = 3	F1:	0.1942524477422683
	P:	0.39739679699001756
	R:	0.1708584877880602
	ACC:	0.6369959633622646
Logistic regression, all features	F1:	0.22522736170125715
	P:	0.47607224321518354
	R:	0.19867322804528276
	ACC:	0.6362534826969592
Random Forest, all features	**F1**:	**0.32633444850345555**
	P:	0.3931869763753829
	R:	0.32897793184535634
	ACC:	**0.6011449077238551**
Random Forest, all features, pruned to depth = 3	F1:	0.0906114249018504
	P:	0.6657277830429393
	R:	0.10079453320911984
	ACC:	0.637645593616744
Decision Tree, highest_education, region, gender, disability, no pruning	F1:	0.11241468166145423
	P:	0.5135856539476726
	R:	0.06559562220794721
	ACC:	0.6790648886074675
Decision Tree, highest_education, region, gender, disability, pruned to depth = 3. *Illustrated in Figure 7.*	F1:	0.09857606225251082
	P:	0.5280882756223184
	R:	0.05486889992465453
	ACC:	0.6808275408470831
Logistic regression, RFE	F1:	0.22326091573672335
	P:	0.44777700838143647
	R:	0.19403827633869203
	ACC:	0.6307807930203678
Random Forest, RFE, no pruning	F1:	0.30227509353062393
	P:	0.33621906995183387
	R:	0.32723513551182004
	ACC:	0.566594144982572
Random Forest, RFE, pruned to depth = 3	**F1**:	**0.14339788733546183**
	P:	0.5248863556150724
	R:	0.13742217881503263
	ACC:	**0.640427955006803**

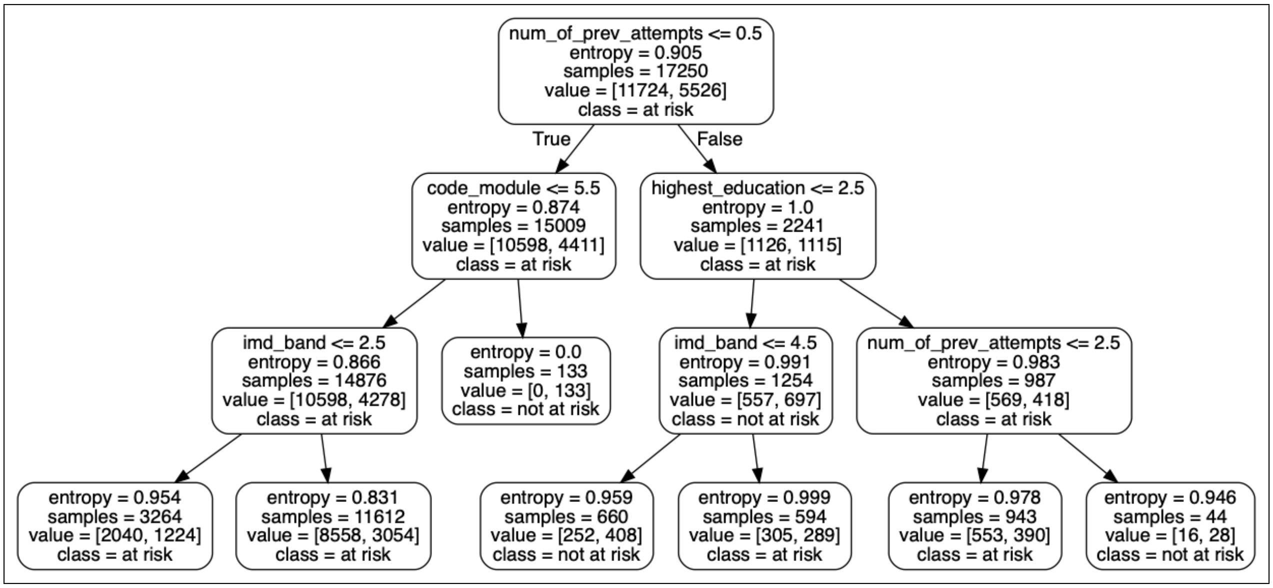


Figure 7: Demographic based decision tree classifier (withdrawn not at risk)

5.2.2 VLE Interaction

Logistic Regression, mean clicks per day	F1:	0.715838193171871
	P:	0.7212950509072961
	R:	0.7114608832840876
	ACC:	0.7980088914969958
SVM, mean clicks per day	F1:	0.7220974641305407
	P:	0.8226623239904555
	R:	0.6439019883771265
	ACC:	0.8228411121874819
Logistic Regression, binary activity per day	F1:	0.7316291147828424
	P:	0.7492935584330797
	R:	0.7152688600202411
	ACC:	0.8124427477588576
SVM, binary activity per day	**F1**:	**0.7413424042386404**
	P:	0.8826494386069681
	R:	0.6393569109038723
	ACC:	**0.840609158133932**

6 Results

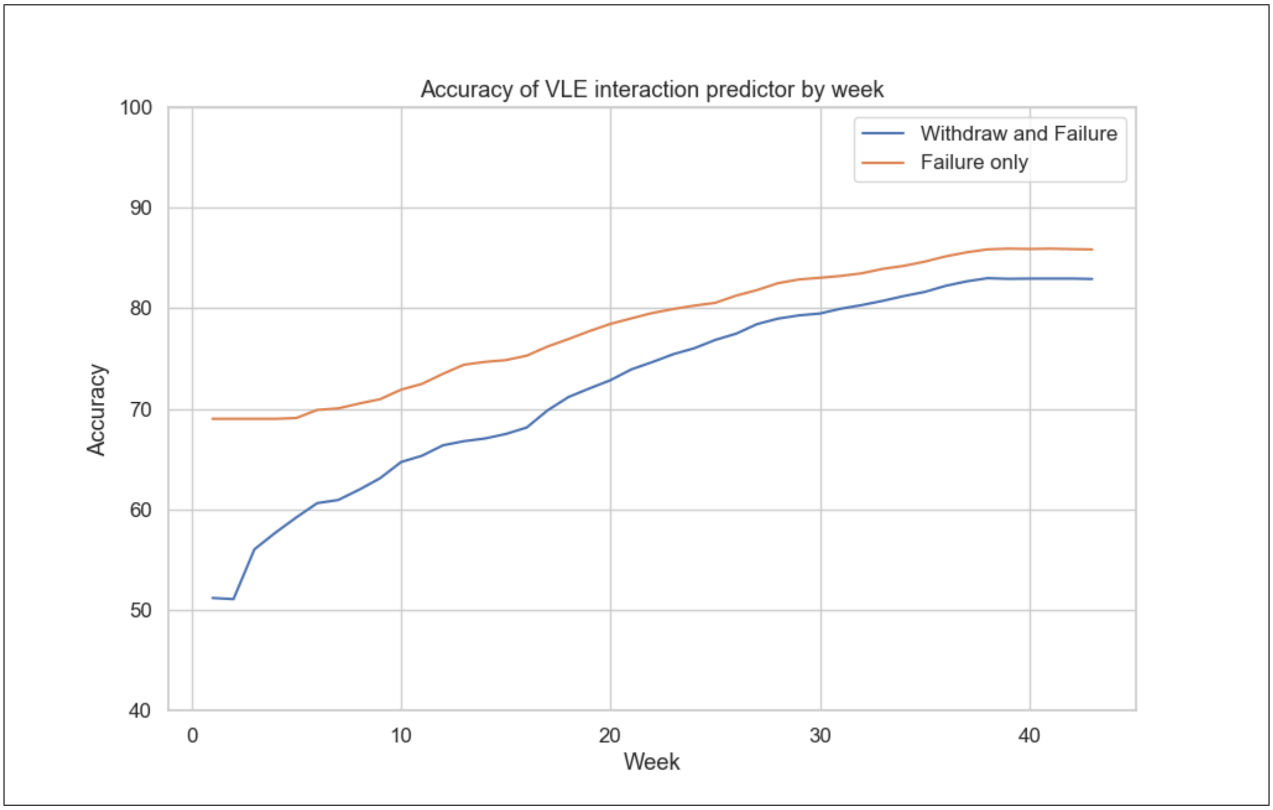


Figure 8: Change in accuracy of classifier over length of course

The goal of this study was to find a means for learning administrators to identify students at risk of failing prior to the end of the course. 8 shows the increase in accuracy of the binary linear regression models as time increases. By week 20 the system is able to identify at risk students with over 70% accuracy whether at risk is defined as withdraw and failure, or solely at risk of failure. The model which only predicts failure performs with a higher accuracy, but both can aide schools at assisting students, and can be used in concert.

7 Conclusion

At the beginning of this experiment I thought that demographics would be a much stronger predictor of success than they turned out to be. The analysis concluded that simply tracking whether a user is frequently active, or not, is the strongest predictor of student success. This is good news for administrators, and developers developing software to identify at risk students. A simply binary log of daily activity is:

1. Easy to develop
2. Inexpensive to store
3. Free of personal data

Discriminating withdraws from failures also did not seem to be necessary for the binary activity classifier. Performance was comparable in both cases. This is good news for administrators interested in maximum retention. Although the causes of each case of non-completion may be different, the symptom of not being active can be identified either way. This allows for first level intervention, triage of sort, to identify what exactly is causing the student's lack of activity and help can be administered whether it be academic, social, or health related. Although SVM had the best performance, it was significantly slower to train than the other models, and its performance gains were modest compared to logistic regression.

8 Future work

Although in this paper I showed that it is a possible, and practical task for learning environment administrators to use data mining techniques to identify at risk students, the work is by no means conclusive or complete. A notable absence is investigation of applying unsupervised learning techniques to this problem. A potential system could use clustering to the activity data in an attempt to identify types of users. It is conceivable that users fall into discrete activity levels, each exhibiting a similar level of risk. This is not explored in this paper, but is a potential area of future work.

Finally, the work has shown that separating withdraw risk from failure risk yields dividends. It would be a worthy use of time to perform this analysis and identify withdraw risk separate from failure risk and develop an independent classifier to help students at risk of withdrawing.