Predicting Student Churn From the University of Washington

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Introduction
Nationally, 30% of undergraduate students do not return for a second year of college. Over $9 is spent in educational expenses on these students. Retention rate is a significant concern due to rising tuition costs and the growing necessity of earning a degree. Universities invest significantly in retention efforts: but identifying at risk students can be difficult. Here, we use data from the UW Registrar’s office in a supervised Machine Learning approach to predict which students will churn (or “drop out”) from the University of Washington. We aim to make our predictions based on data acquired after only a single quarter of being a student. We aim to identify at risk students early, when Universities will still be able to make impactful retention efforts.

Methods
• Prepare Data
  • Sample equal amounts completion/non-completion for a balanced data set
  • Filter out Tacoma & Bothell students: restrict data to 1998-2016 enrollees
  • Categorize data (first quarter GPA, first quarter classes, demographics, high school performance)
• Run parameter sweeps using KFCV
• Establish initial machine learning models using intuitive features
  • Logistic Regression
  • K-Nearest Neighbors
  • Random Forest
• Evaluate performance of each model

Results

Demographic Features:

<table>
<thead>
<tr>
<th>Race</th>
<th>Completion</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>African American</td>
<td>72.80%</td>
<td>2011</td>
</tr>
<tr>
<td>American Indian</td>
<td>71.40%</td>
<td>938</td>
</tr>
<tr>
<td>Asian</td>
<td>81.40%</td>
<td>16037</td>
</tr>
<tr>
<td>Caucasian</td>
<td>79.70%</td>
<td>39442</td>
</tr>
<tr>
<td>Race Not Known</td>
<td>79.90%</td>
<td>10242</td>
</tr>
<tr>
<td>Resident</td>
<td>80.50%</td>
<td>6290</td>
</tr>
<tr>
<td>Non Resident</td>
<td>74%</td>
<td>7828</td>
</tr>
</tbody>
</table>

Table 1: Lists of demographic variables in dataset: splits of graduation vs non-graduation and number of students in each category – note that race and residency are not exclusive

First Quarter Performance:

![Figure 1: Color map showing distribution of completion at various GPAs earned and credits taken. Note that higher GPAs and more credits taken graduate more often.](image1)

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Initial Machine Learning Models (On balanced dataset)
• Parameter Sweeps (10 fold cross validation):
  • LogReg: .01 regularization parameter (100x overfit)
  • K-Nearest Neighbors: 36 neighbors
  • Random Forests: 36 Trees

Model Performance (70-30 train test split)
• LogReg: 66.59% accuracy (.729 AUC)
• K-Nearest Neighbors: 64.60% accuracy (.660 AUC)
• Random Forests: 62.24% accuracy (.694 AUC)

ROC Curves:

![Figure 2: Performance in terms of Operating Characteristic Curves (ROC). We can see that LogReg is the most accurate algorithm.](image2)

Figure 2: Performance in terms of Operating Characteristic Curves (ROC). We can see that LogReg is the most accurate algorithm.

Predicting Length of Stay
• Linear Regression to predict when dropouts leave school
• RMSE of ~5 quarters

Conclusions
• 16% boost over baseline accuracy
• Concerns of heterogeneity of student population
• Data does not cover important facets of student life
• Logistic Regression is the best performing algorithm

Acknowledgements: We would like to thank the UW registrar’s office for providing anonymized student data for the purpose of these experiments