Using Multiple Measures to Enhance Student Placement

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Growing body of evidence


• 20-35% of students severely underplaced with many more underplaced [Scott-Clayton & Belfield, 2015] [bit.ly/CCRCPlacementAccuracy]

• Even in selective four year institutions
  – Underestimates students of color, women, first generation college students, low SES: (Hiss & Franks, 2014) [bit.ly/DefiningPromise]
Figure 10
Relative Weight of High School GPA and SAT Scores, Before and After Controlling for SES, in Predicting 5-Year Graduation: All UC Freshmen vs. Underrepresented Minorities, 1994 to 2005

Source: UC Corporate Student System data, 1994 to 2005. All estimates are statistically significant at .001 confidence level.
The case for multiple measures

- Basic methodological principles of assessment
- Evidence for potential reduction of error and increase success rates and sequence completion
Long thread of research in the CCCs

  – 11th grade HS variables as early alert

  – self-reported HS variables as powerful predictors of completion

  – HSGPA & grades strong predictors of performance

  – replication of LBCC research with 12 additional colleges (STEPS)
MMAP Project Overview

bit.ly/MMAP2015

- Collaborative effort of CCCCCO, Common Assessment Initiative (CAI), Cal-PASS Plus, RP Group and now 31CCCs
  - Develop, pilot, and evaluate implementation of multiple measures placement tools
    - Including high school transcript data, and in 2015-2016 non-cognitive variable data & self-reported HS transcript data
  - English, Math, and coming in 2015-2016, Reading and ESL
  - Engage pilot colleges to conduct local replications, test models and pilot use in placement, and provide feedback
Decision Trees

- Howard Raiffa explains decision trees in *Decision Analysis* (1968).
  - Inspired by Hunt and others’ work in the 50’s & 60’s
- CART popularized by Breiman et al. in mid-90’s
  - Based on information theory rather than statistics; developed for signal recognition
- Today we will discuss recursive partitioning and regression trees (i.e., ‘rpart’ for R).
Increasing Homogeneity with each split
Pros and Cons of Decision Trees

**Strengths**
- Visualization
- Easy to understand output
- Easy to code rules
- Model complex relationships easily
- Linearity, normality, not assumed
- Handles large data sets
- Can use categorical and numeric inputs

**Weaknesses**
- Results dependent on training data set – can be unstable esp. with small N
- Can easily overfit data
- Out of sample predictions can be problematic
- Greedy method selects only ‘best’ predictor
- Must re-grow trees when adding new observations
How is heterogeneity measured?

- Gini-Simpson Index

\[ 1 - \lambda = 1 - \sum_{i=1}^{R} p_i^2 = 1 - 1/2D \]

- If selecting two individual items randomly from a collection, what is the probability they are in different categories.

- The Gini coefficient is a measure of the inequality of a distribution, a value of 0 expressing total equality and a value of 1 maximal inequality.
Key considerations

• Splitting criterion: how small should the leaves be? What are the minimum # of splits?
• Stopping criterion: when should one stop growing the branch of the tree?
• Pruning: avoiding overfitting of the tree and improving
• Understanding classification performance
Two approaches to avoid overfitting

- **Forward pruning:** Stop growing the tree earlier.
  - Stop splitting the nodes if the number of samples is too small to make reliable decisions.
  - Stop if the proportion of samples from a single class (node purity) is larger than a given threshold

- **Post-pruning:** Allow overfit and then post-prune the tree.
  - Estimation of errors and tree size to decide which subtree should be pruned.
Libraries and Code for R: Loading and subsetting data

#Load data
MMAPMath <- read.csv("C:/Folder/MMAPMath.csv", header=T)

#package that creates subsets
require(dplyr)

m5stat <- filter(MMAPMath,
 HS_GPA_PRESENT_BY GRADE == 1111,
 CC_FIRST_LEVEL_RANK == 0, CC_STATISTICS == 1)
Basic Classification Decision Tree

# CART packages
library(rpart)
library(rpart.plot)

# set control parameter
ctrl <- rpart.control(minsplit = 100, cp = 0.0015, xval = 10)

cartfit_m5statpoisson <- rpart(formula = CC_FIRST_COURSE_SUCCESS_IND ~ HS_11_GPA_CUM + PRE_ALG_ANY_C + ALG_I_ANY_C + ALG_II_ANY_C + GEO_ANY_C + TRIG_ANY_C + PRE_CALC_ANY_C + CALC_ANY_C + STAT_ANY_C + STAR_MATH_EAP_IND + HS_EXIT_SUBJ_TO_CC_ENTRY_SUBJ + AP_ANY_C + [CST score and subscale variables]
  ,data = m5stat
  ,method="poisson" ← Change method here to test different distributions
  ,control=ctrl)
Splitting Methods

- Class = used for categorical dependent var
- ANOVA = used for continuous dependent var
- Poisson = used for count of events in time frame such as survival data
- Exponential = can also be used for survival with different distributional assumptions
CART Output and Diagnostics

```r
varimp(m5poisson)
print(cartfit_m5statpoisson)
rsq.rpart(cartfit_m5statpoisson)
prp(cartfit_m5statpoisson,main="Transfer Level Statistics, 11th Grade Data, with CST detail, Poisson",extra=100) m5poisson
```
Testing Other Models using CARET

#load libraries
library("caret")
library("e1071")

Create training and test sets (code omitted here)

#CARET model
cartfit_m5stat <- CC_FIRST_COURSE_SUCCESS_IND ~
HS_11_GPA_CUM + PRE_ALG_ANY_C + ALG_I_ANY_C + ALG_II_ANY_C + GEO_ANY_C +
TRIG_ANY_C + PRE_CALC_ANY_C + CALC_ANY_C + STAT_ANY_C + STAR_MATH_EAP_IND +
HS_EXIT_SUBJ_TO_CC_ENTRY_SUBJ + AP_ANY_C + [CST score and subscale variables]
, data = training_m5stat
, method = "rpart"  ← Change method here to test different models (reg, svm, etc.)
, trControl = ctrl
, preProc = c("center", "scale")  OPTIONAL if to standardize variables
, tuneLength = 10)
MMAP variables for predicting CC success

English

- Cumulative HS GPA
- AP English class grade
- Score on English CST
- Grade in last English class

Math

- Cumulative HS GPA
- Grade in Algebra I, Algebra II, Statistics, Trigonometry, Calculus
- Taking a challenging CST
- Score on math CST
Using Multiple Measures to Enhance Student Placement, CAIR 2015
Statistics Tree – NDM

- **HS\_12\_GPA\_CUM >= 3**
  - **HS\_12\_GPA\_CUM >= 2.6**
    - **PRE\_CALC\_ANY\_C >= 0.5**
      - **STAT\_ANY\_C >= 0.5**
        - **HS\_12\_GPA\_CUM >= 2.3**
          - 0.34 (8%)
          - 0.43 (10%)
        - 0.57 (2%)
        - 0.56 (3%)
    - **PRE\_CALC\_ANY\_C < 0.5**
      - **STAT\_ANY\_C >= 0.5**
        - **HS\_12\_GPA\_CUM >= 2.3**
          - 0.34 (8%)
          - 0.43 (10%)
        - 0.57 (2%)
        - 0.56 (3%)
      - 0.75 (28%)
      - 0.9 (28%)
- **HS\_12\_GPA\_CUM < 3**
  - 0.68 (7%)
  - 0.66 (4%)
  - 0.54 (13%)
  - 0.57 (2%)
  - 0.66 (4%)
  - 0.58 (3%)
  - 0.54 (13%)
  - 0.57 (2%)
  - 0.68 (7%)
  - 0.75 (28%)
  - 0.9 (28%)
<table>
<thead>
<tr>
<th><strong>English Decision Rules</strong></th>
<th><strong>Direct matriculants</strong></th>
<th><strong>Non-direct matriculants</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Transfer-level</strong></td>
<td>HS 11 GPA &gt;= 2.6</td>
<td>HS 12 GPA &gt;= 2.6</td>
</tr>
<tr>
<td>(criterion = 0.70 / 0.70)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>One-level below</strong></td>
<td>HS 11 GPA &gt;= 2.3</td>
<td>HS 12 GPA &gt;= 2.2 &amp;</td>
</tr>
<tr>
<td>(criterion = 0.65 / 0.65)</td>
<td></td>
<td>HS 12 English course GPs &gt;= 1.8</td>
</tr>
<tr>
<td><strong>Two-levels below</strong></td>
<td>HS 11 GPA &gt;= 2.0</td>
<td>HS 12 GPA &gt;= 1.8 &amp;</td>
</tr>
<tr>
<td>(criterion = 0.60 / 0.55)</td>
<td></td>
<td>HS 12 English course GPs &gt;= 1.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>HS 12 GPA &gt;= 1.8 &amp; CST &gt;= 288</td>
</tr>
<tr>
<td><strong>Three-levels below</strong></td>
<td>HS 11 GPA &gt;=1.4</td>
<td>HS 12 GPA &gt;=1.5 &amp; CST&gt;=268</td>
</tr>
<tr>
<td>(criterion = 0.55 / 0.55)</td>
<td></td>
<td>HS 12 GPA &gt;=1.7</td>
</tr>
<tr>
<td><strong>Four-levels below</strong></td>
<td>Everyone else</td>
<td>Everyone else</td>
</tr>
</tbody>
</table>

*HS* is the student’s high school (11th or 12th grade). GPA is the grade point average.
Using Multiple Measures to Enhance Student Placement, CAIR 2015

Placement into Transfer-level with Current Placement Systems vs. Strong Multiple Measures (Statewide)

- English: Current (38%) vs. Disjunctive MM (61%)
  - Current: (n=103,510)
  - Disjunctive MM: (n=103,510)

- Math: Current (31%) vs. Disjunctive MM (42%)
  - Current: (n=143,253)
  - Disjunctive MM: (n=143,253)
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Transfer Level Math Placement by Ethnicity

<table>
<thead>
<tr>
<th>Ethnicity</th>
<th>Current</th>
<th>Disjunctive MM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Afr Am</td>
<td>15%</td>
<td>22%</td>
</tr>
<tr>
<td>Latino</td>
<td>21%</td>
<td>32%</td>
</tr>
<tr>
<td>Asian</td>
<td>41%</td>
<td>53%</td>
</tr>
<tr>
<td>White</td>
<td>51%</td>
<td>65%</td>
</tr>
</tbody>
</table>
Progress to date

• 31 total pilot colleges signed up
  – Allowed to proceed at institutionally appropriate pace
  – 5 districts representing 9 colleges with pilots in the field in Fall 2015
  – 10 targeting Spring 2016 implementation
SDCCD MMAP F2015 Pilot (N = 941)

Why is this important to your college and the state?

• General evidence of severe underplacement
  – On average, 1-2 superfluous semesters of development education

• Direct costs

• Opportunity costs

• Not just a community college issue

• ~2,000,000 CCC students
  – ~400,000 first-time
  – >75% assigned to remediation

• ~400,000 CSU Students
  – ~60,000 first-time
  – >30% assigned to remediation

• ~200,000 UC Students
  – ~60,000 first-time
  – equity and outcome considerations
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http://www.rpgroup.org/projects/multiple-measures-assessment-project