How Machine Learning and Multiple Measures are Reshaping College Placement

Terrence Willett, John Hetts, Craig Hayward

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Acknowledgements

- Current and former MMAP team members
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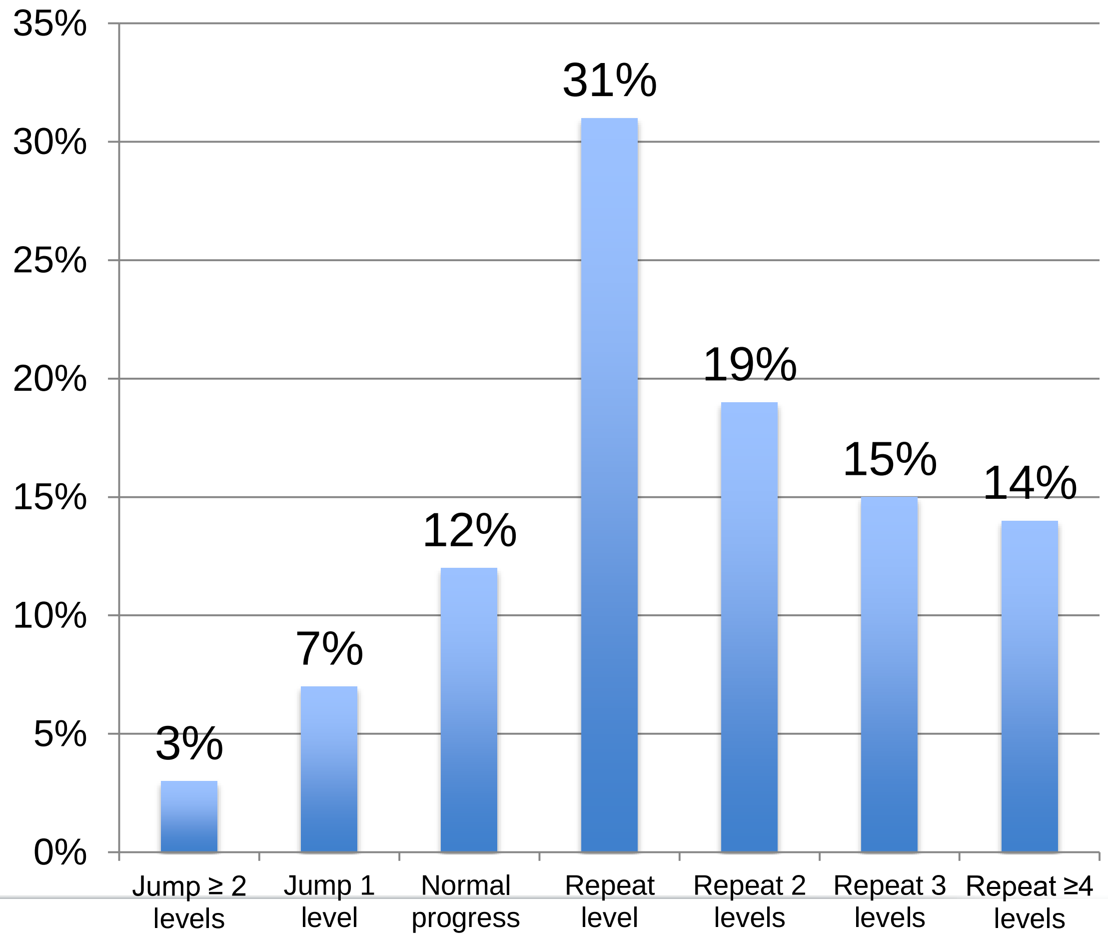
- Common Assessment Initiative Steering Committee
- Pilot colleges
- High School participants
- California Community College Chancellor's Office MIS team

Transitions and intersegmental trust

- Within systems: highly reliable progression after successful completion
- Between systems – different story
- HS to CSU
  - 38% repeat previously completed coursework, ~60% African Americans, 45% of Hispanics
- HS to CCC transition
  - ~3/4 repeat ≥ 1 level, ~1/2 repeat ≥ 2 levels of math
  - African Americans & Hispanics ~60% more likely, Female students ~20% more likely
- Noyce Foundation report
  - Algebra in 8th grade, ~2/3 repeat including 50% of students with B or better
  - Algebra in 7th grade advance to Geometry in 8th grade

HS to CCC Math transition



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Data Set for the Models

- California Community College (CCC) students enrolled in an English, Math, Reading or ESL class with matching high school data in California Partnership for Achieving Student Success (CalPASS) statewide intersegmental database
  - ~1 M cases for Math & English; ~200k for Reading & ESL
- Bulk of first CCC enrollments from 2008 through 2014
- Rules were developed with the subset of students who had four years of high school data (about 25% of total sample)
- Used machine learning ***rpart*** package in R to create decision trees
  – http://rpgroup.org/Our-Projects/All-Projects/Multiple-Measures/PilotCollegeResources see Decision Rules and Analysis Code -> Using R for Creating Predictive Models
- R4IR Tutorial https://drive.google.com/drive/folders/0Bz-jqwGzLQjJajA5YUIxUjdETzA?usp=sharing

Variables Explored in the Models

- High School Unweighted Cumulative GPA
- Grades in high school courses
- CST scores
- Advanced Placement course taking
- Taking higher level courses (math)
- Delay between HS and CCC (math)
- HS English types (expository, remedial, ESL)
- HS Math level (Elem. Algebra, Integrated Algebra, Pre-Calculus)

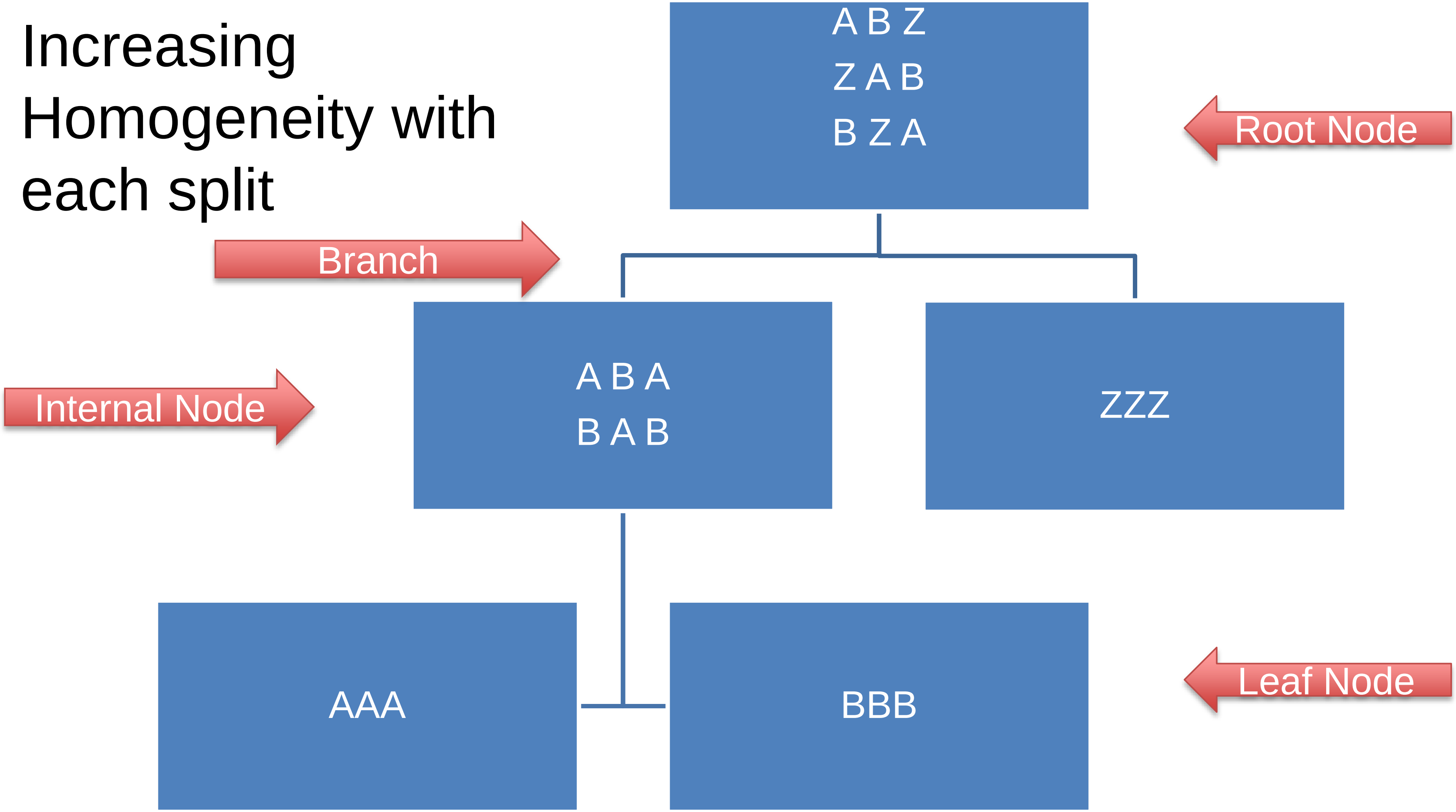
What are Decision Trees?

- Howard Raiffa explains decision trees in Decision Analysis (1968).
- Ross Quinlan invented ID3 and introduced it to the world in his 1975 book, Machine Learning.
- CART popularized by Breiman et al. in mid-90's
  - Breiman, L., Friedman, J., Olshen, R., & Stone, C. (1994). *Classification and regression trees.* Chapman and Hall: New York, New York.
  - Based on information theory rather than statistics; developed for signal recognition

Engineering Flowchart

DOES IT MOVE?

Increasing Homogeneity with each split



How is homogeneity measured?

$$D = 1 - \sum_{i=1}^{n} p_i^2$$

- Gini-Simpson Index
- p-square = probability of two items taken at random from the set being of same types; D=dissimilarity/diversity
- Proposed by Corrado Gini in 1912 as a measure of inequality of income or wealth; used in demographics and ecology as diversity index
- If selecting two individual items randomly from a collection, what is the probability they are in different categories.
- Other indices such as Shannon-Wiener can also be used

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

Loading Data in R

```
#set working directory for location of data
setwd("C:/Users/Me/Documents/MMAPData")
#Load data
MMAPMath <- read.csv(“C:/Folder/MMAPMath.csv", header=T)
#save data and analyses to working directory
save.image(“MMAPMath.RData")
```

http://rpgroup.org/Portals/0/Documents/Projects/MultipleMeasures/DecisionRulesandAnalysisCode/Instructions-for-Using-R-to-Create-Predictive-Models-v5.pdf

Basic Classification Decision Tree

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

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

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) ← Change control specs here
```

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

- printcp(cartfit_m5statpoisson) ← **shows relative error by cp value**
- print(cartfit_m5statpoisson) ← **indented text print out of tree**
- rsq.rpart(cartfit_m5statpoisson) ← **graph showing error by # splits**
- prp(cartfit_m5statpoisson,main="Transfer Level Statistics” ,extra=100,varlen=0,left=FALSE) ← **graph tree**

Pros and Cons of Decision Trees

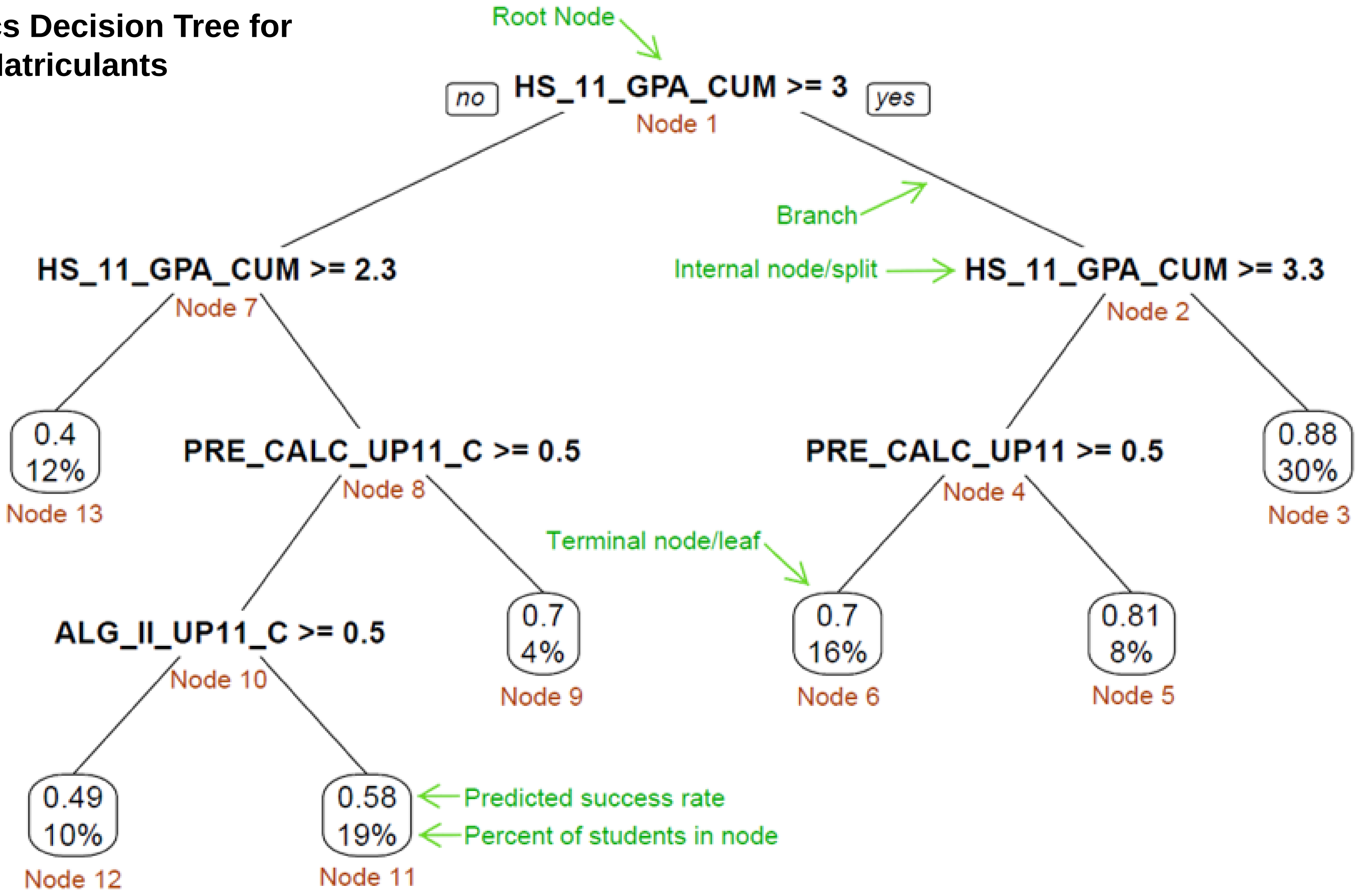
Strengths

- 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

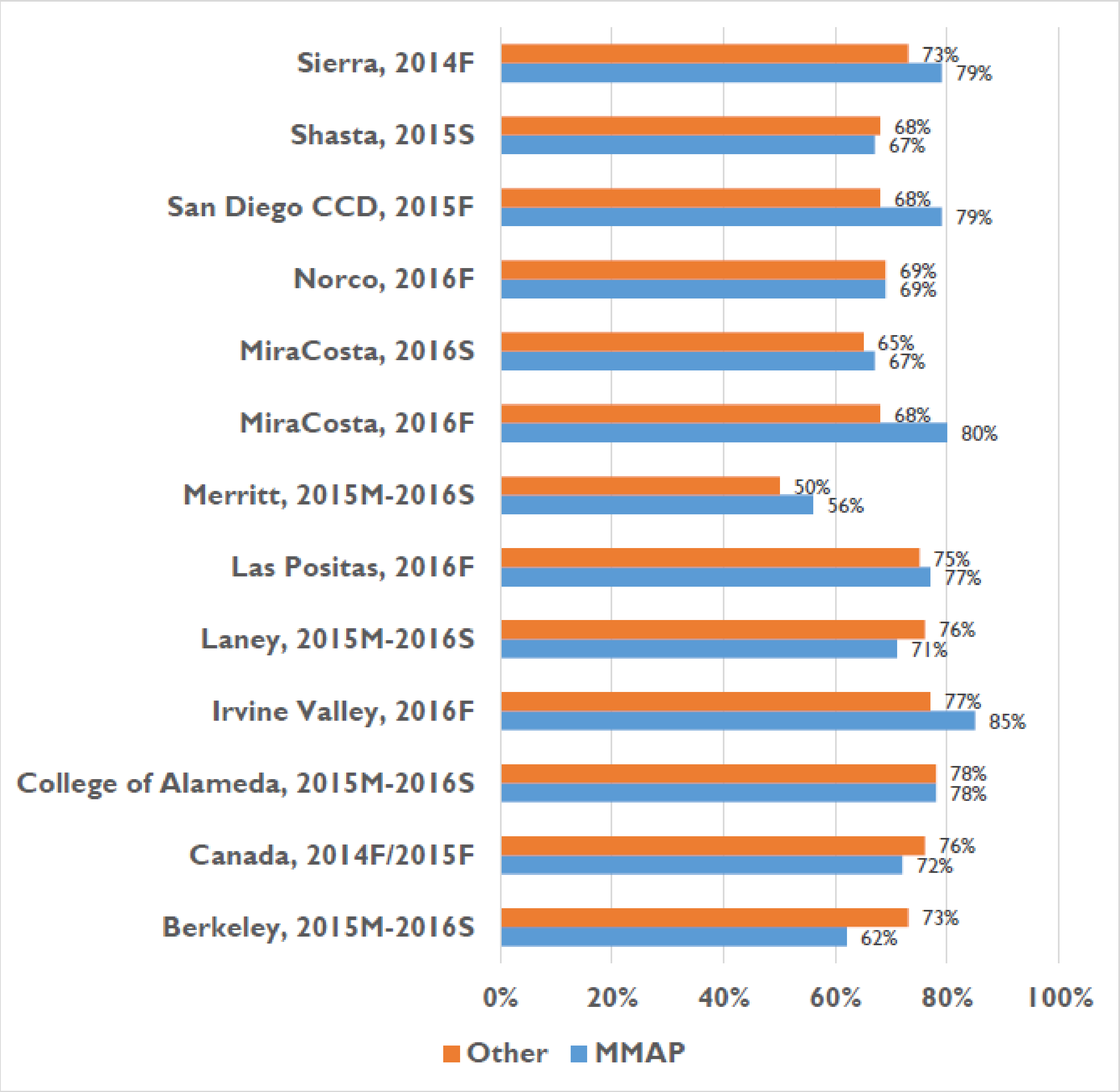
Statistics Decision Tree for Direct Matriculants



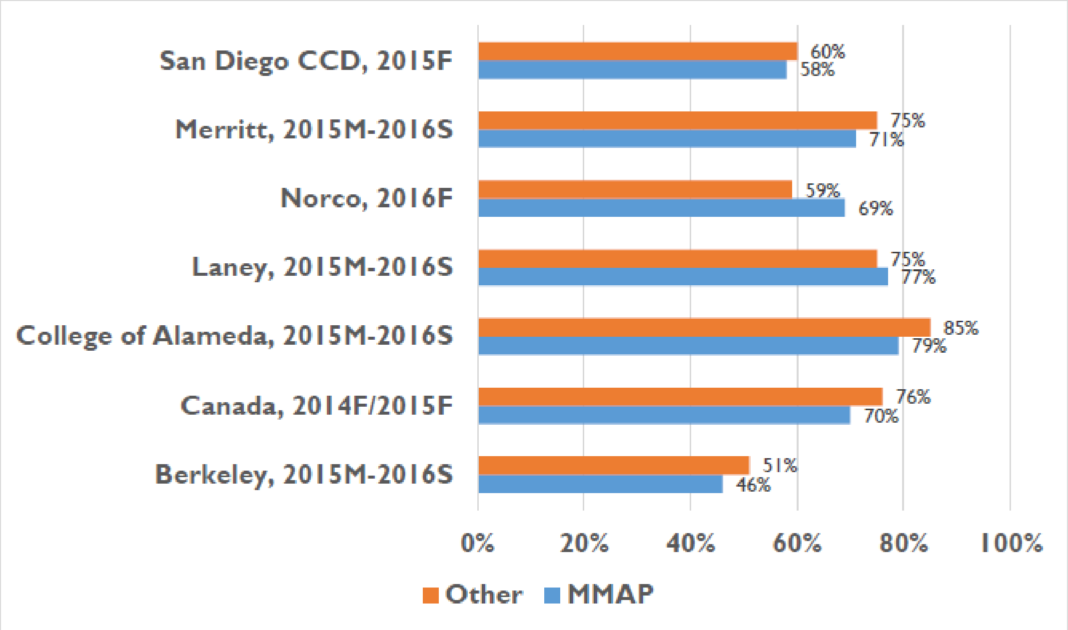
MMAP Transfer-Level Placement Recommendations

Transfer Level Course	Direct Matriculant	Non-Direct Matriculant
College Algebra (STEM) *Passed Algebra II (or better)*	HS 11 GPA >=3.2 OR HS 11 GPA >=2.9 AND Pre-Calculus C (or better)	HS 12 GPA >=3.2 OR HS 12 GPA >=3.0 AND Pre-Calculus or Statistics (C or better)
Statistics (General Education/Liberal Arts) *Passed Algebra I (or better)*	HS 11 GPA >=3.0 OR HS 11 GPA >=2.3 AND Pre-Calculus C (or better)	HS 12 GPA >=3.0 OR HS 12 GPA >=2.6 AND Pre-Calculus (C or better)
English	HS 11 GPA >=2.6	HS 12 GPA >=2.6

Success Rates in Transfer-level English



Success Rates in Transfer-level Math

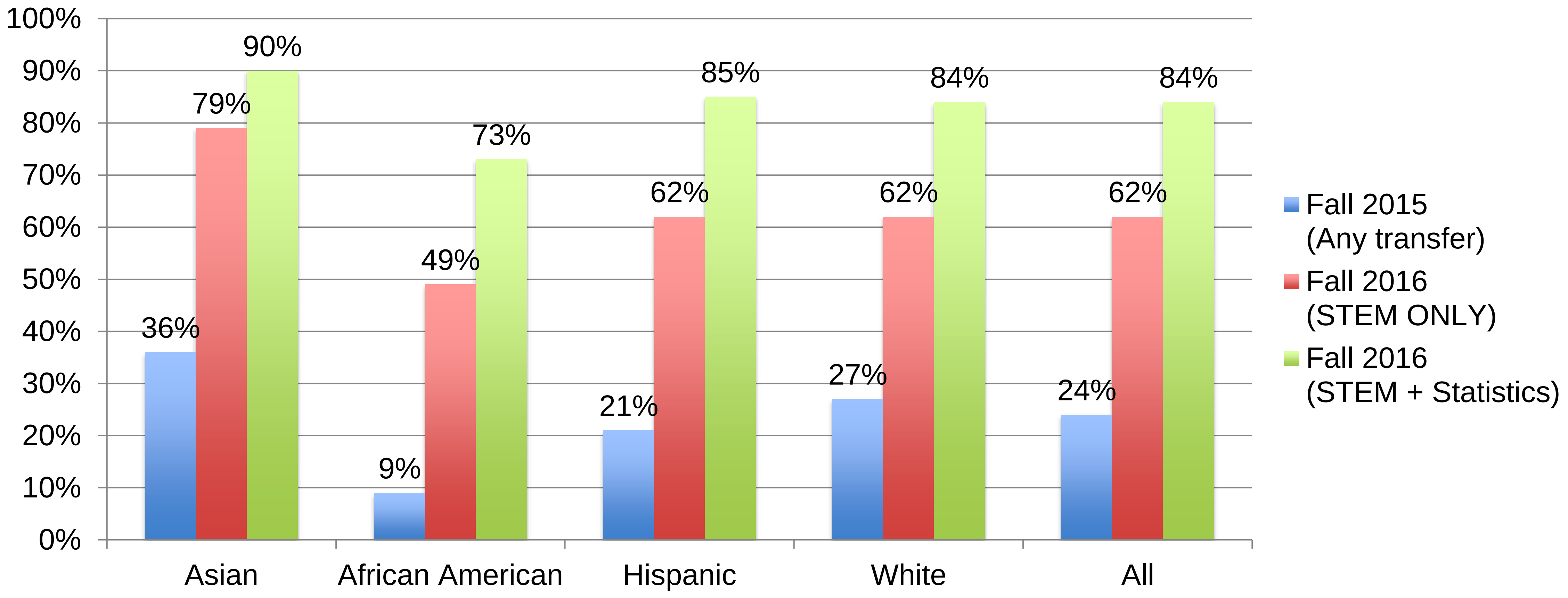


"Under our previous policies, African American and Latino students were far less likely to place into transfer-level math. Under the new policies, African American students' access to transfer-level math increased eight-fold, Latino students' access increased four-fold, and the disproportionate impact in placement was eliminated for all racial groups."
– Cuyamaca College

"There are thousands of reasons to do this; each one has a name."
– Bakersfield College

"MMAP is a COMPLETION initiative, not a SUCCESS initiative."
– Santa Monica College

Transfer level placement by year/method in Math at Cuyamaca



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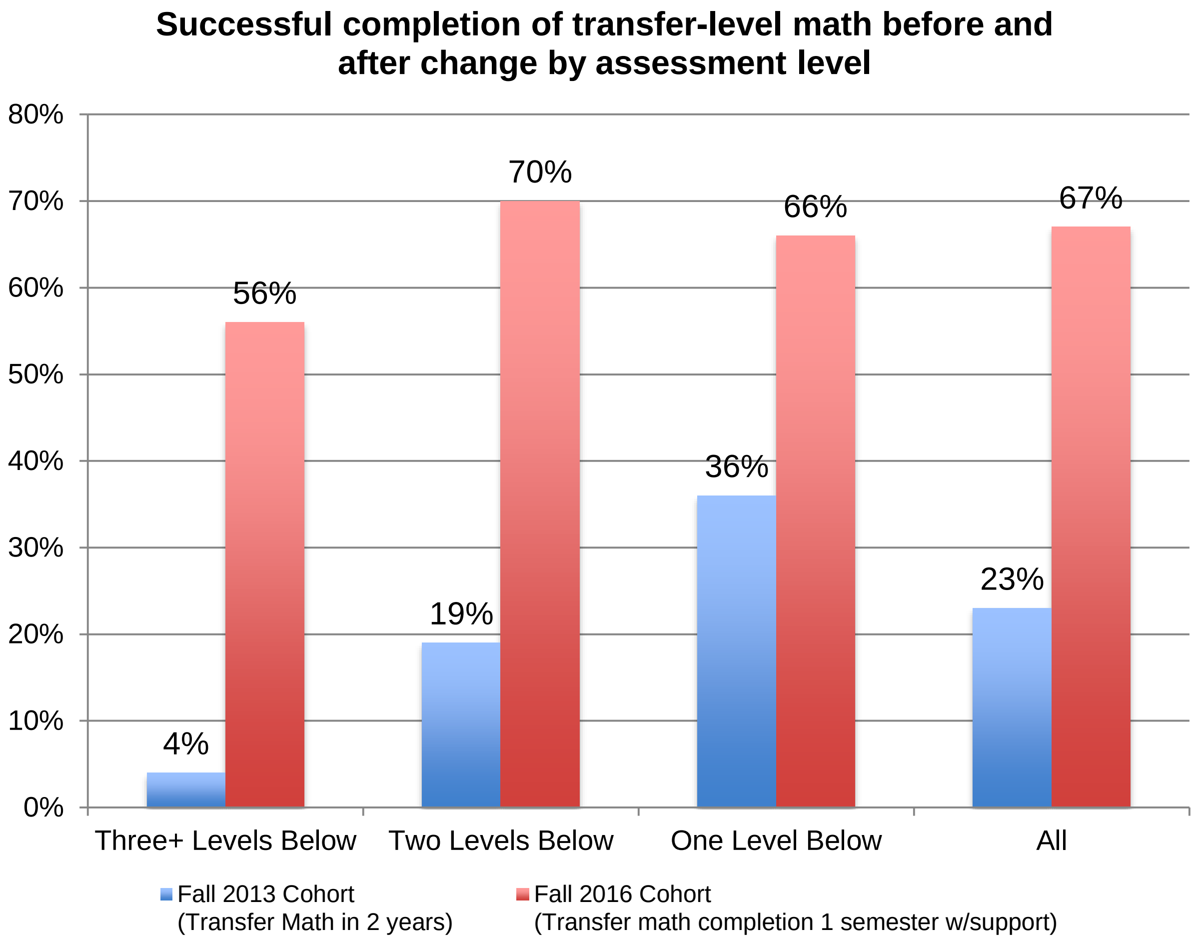
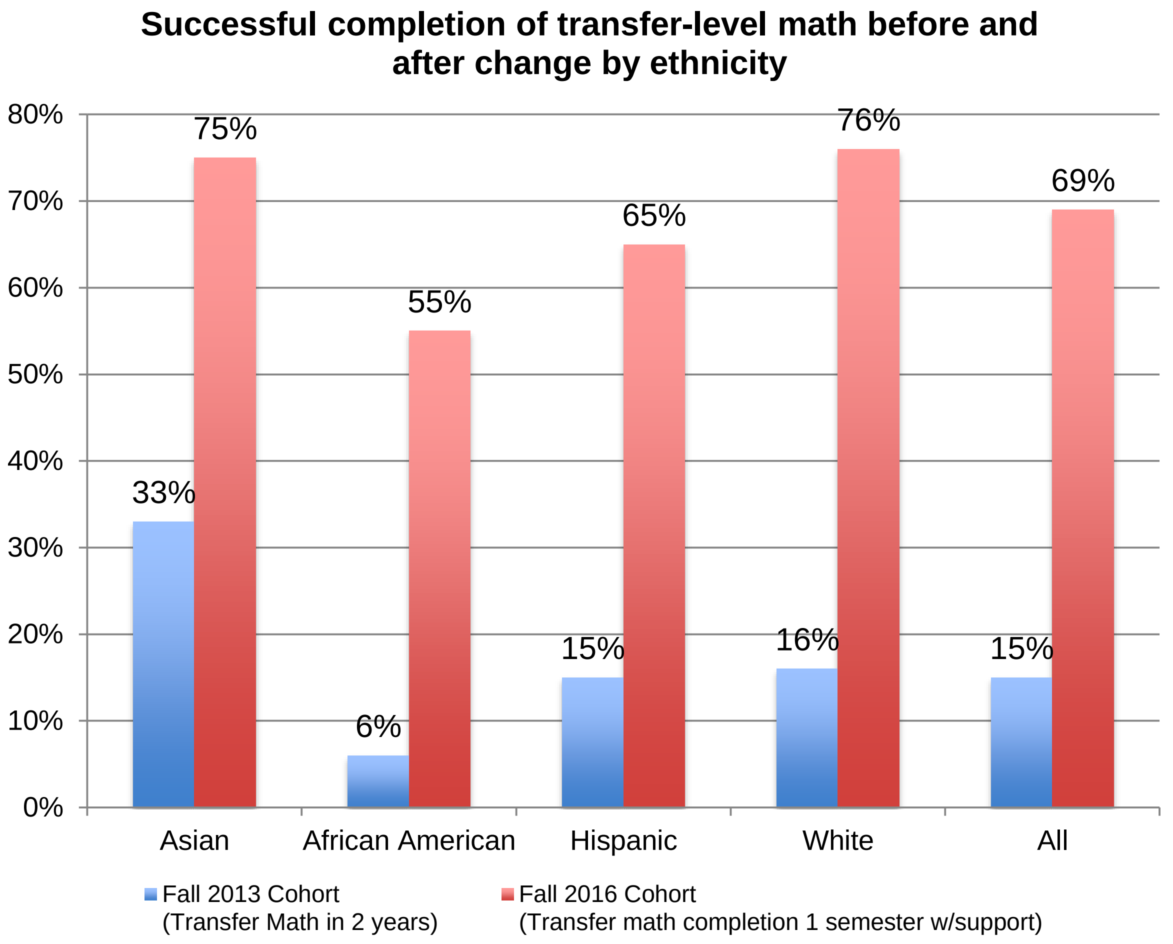
Gateway momentum in Math at Cuyamaca





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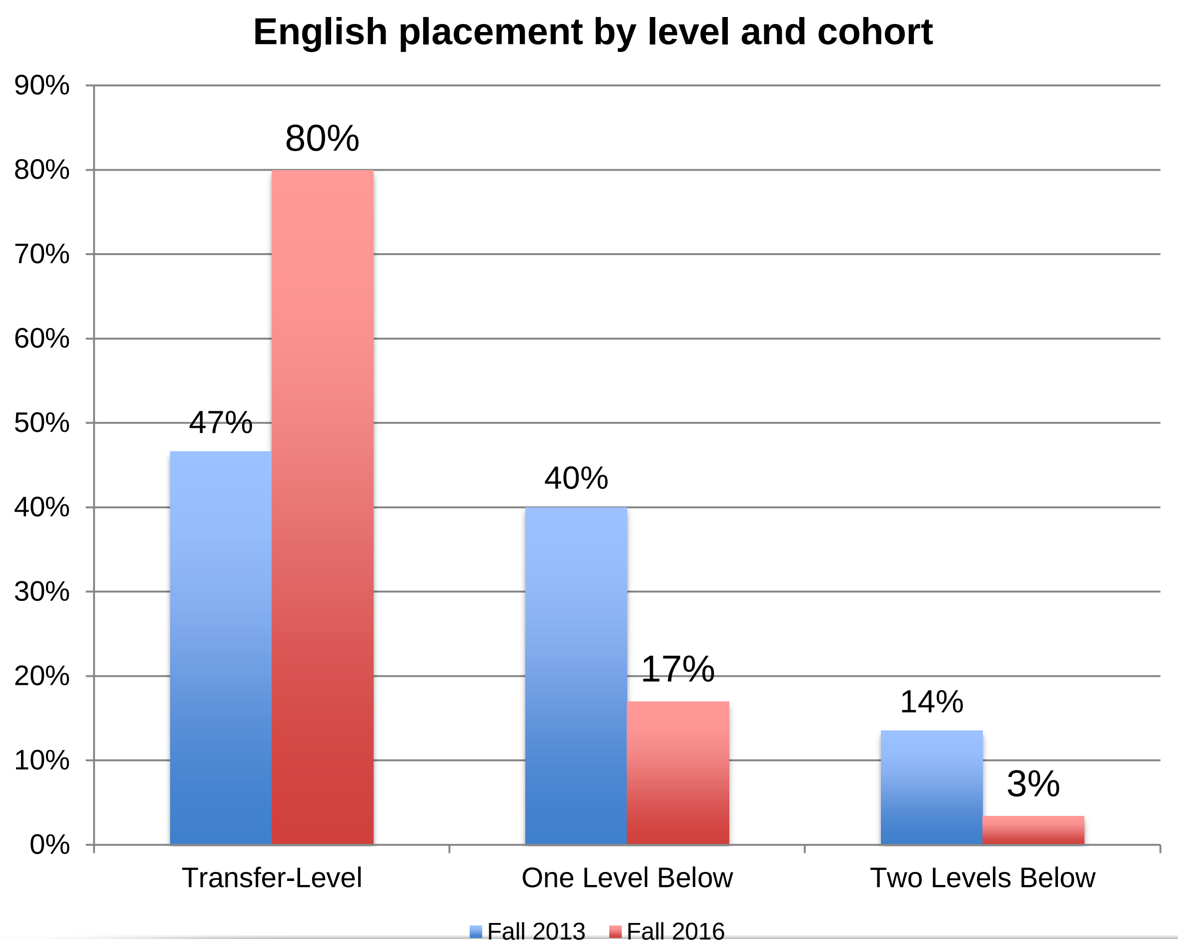
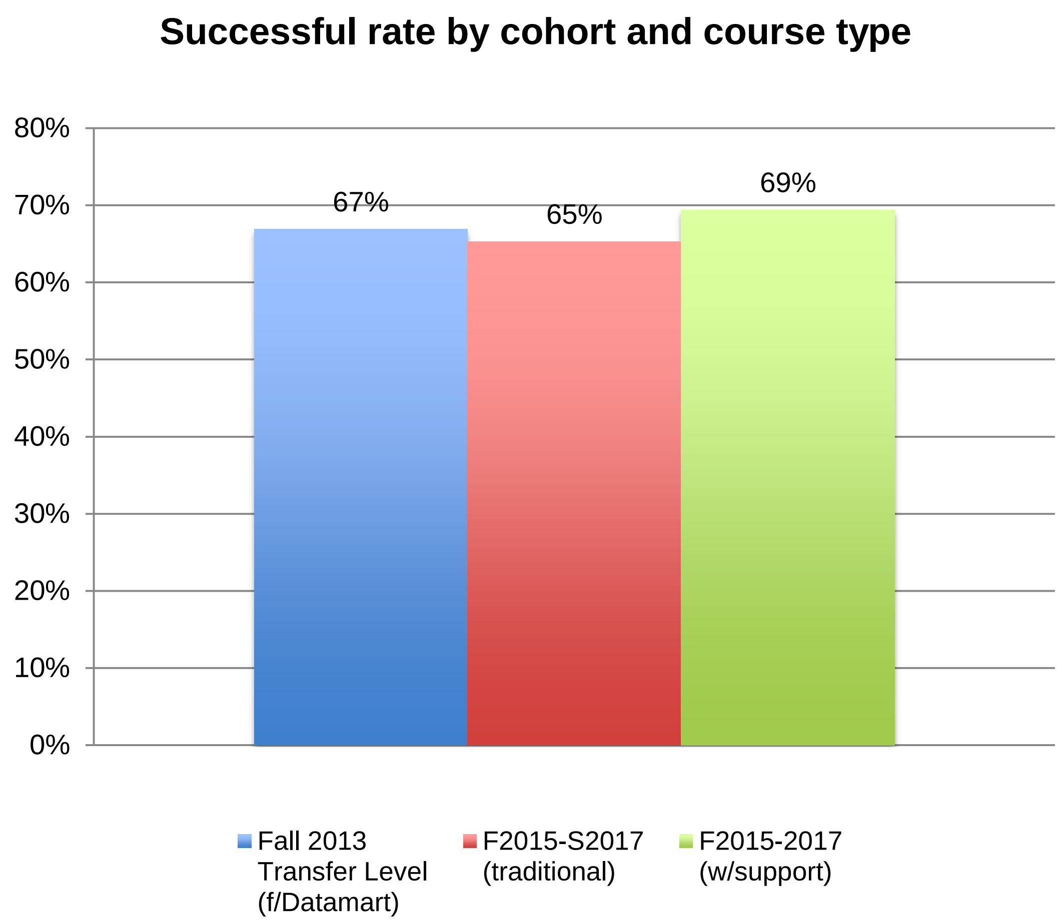
Gateway momentum in English at Skyline





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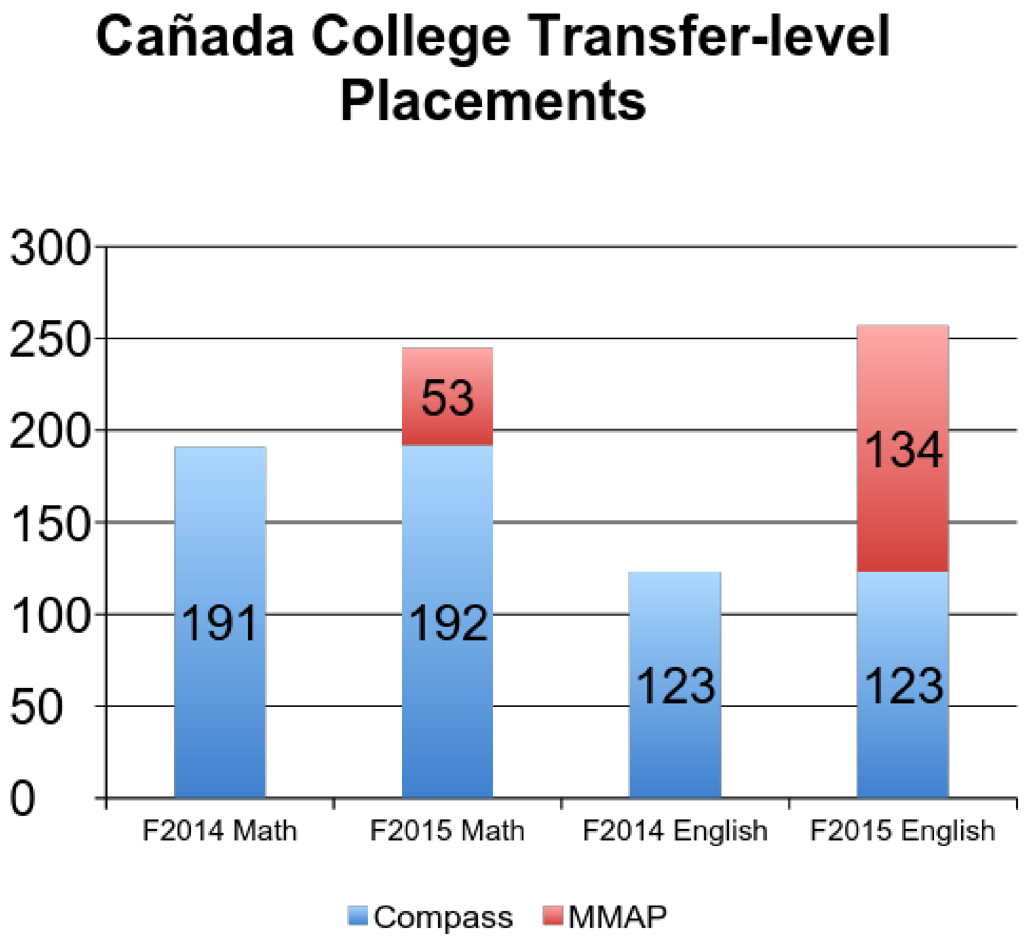
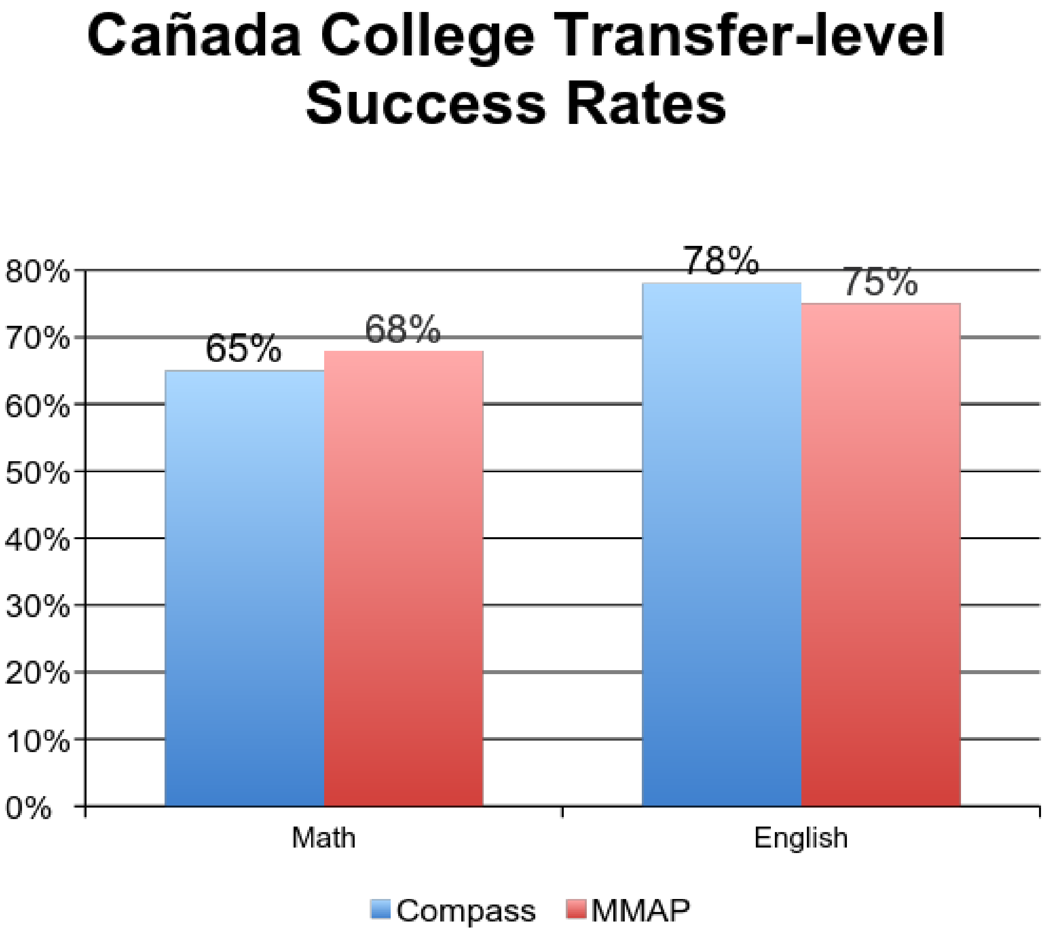
Fall 2015:Cañada College





Rule set: English = 2.3 AND B- or better; Math = 3.2 AND C or better

bit.ly/MMAPPilotLessons

Various Placement Systems and Their Impact on Student Equity

Placement Error

- **Overplacement:** Student is placed above their ability to succeed. Highly visible.

- **Underplacement:** Student could have been successful at a higher level than where placed. Tends to be invisible.

- Current placement systems tend to result in much greater underplacement error.

Evaluating Placement Systems

Disjunctive placement:

Take the highest placement (Test or MMAP)

Recommended by MMAP

Compensatory placement:

Logistic regression (combines Test, MMAP simultaneously)

Run with two cut-values: 0.70, 0.50

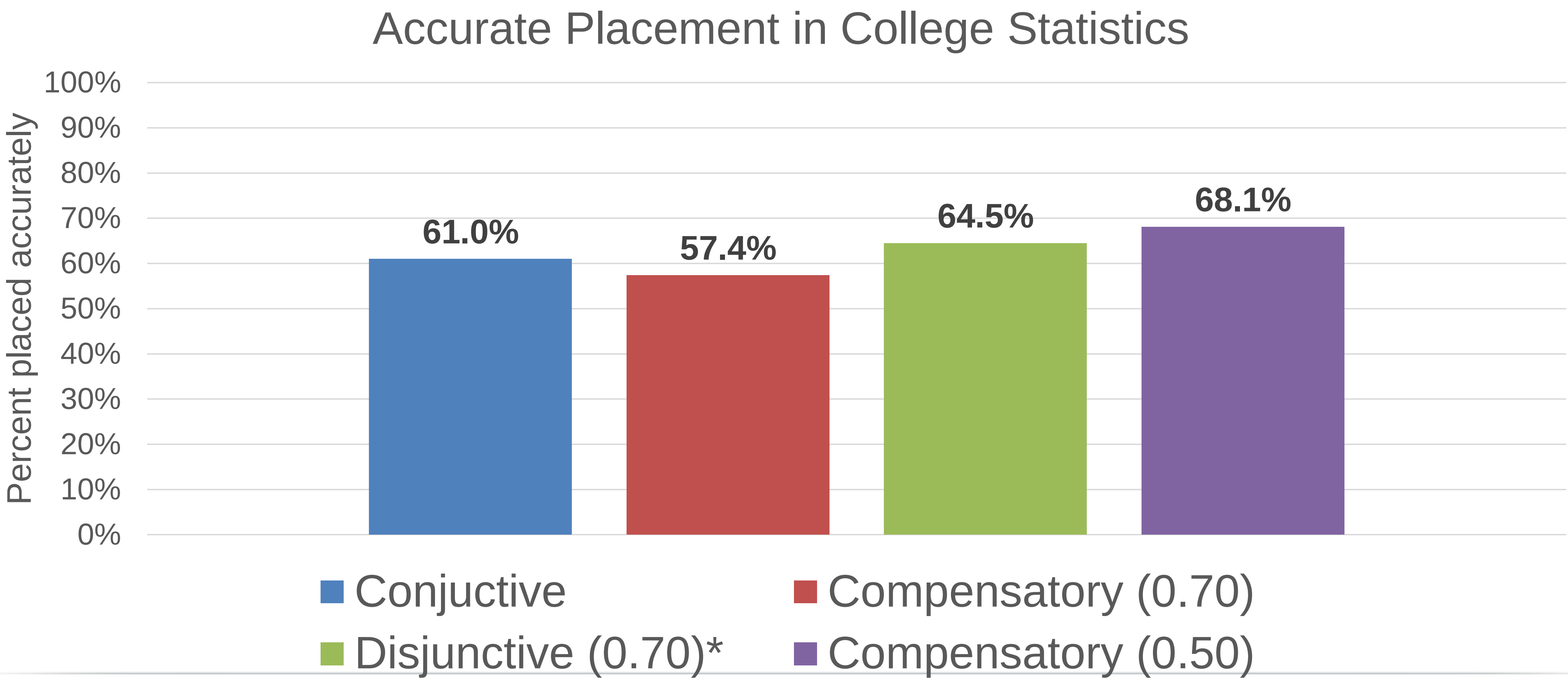
Conjunctive placement:

Only if Test and MMAP in agreement

Highly restrictive

Not recommended by the CCCCO

Accuracy: College Statistics Placement



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*Negatives are unknown for the disjunctive models, so accuracy cannot be completely calculated for disjunctive model.

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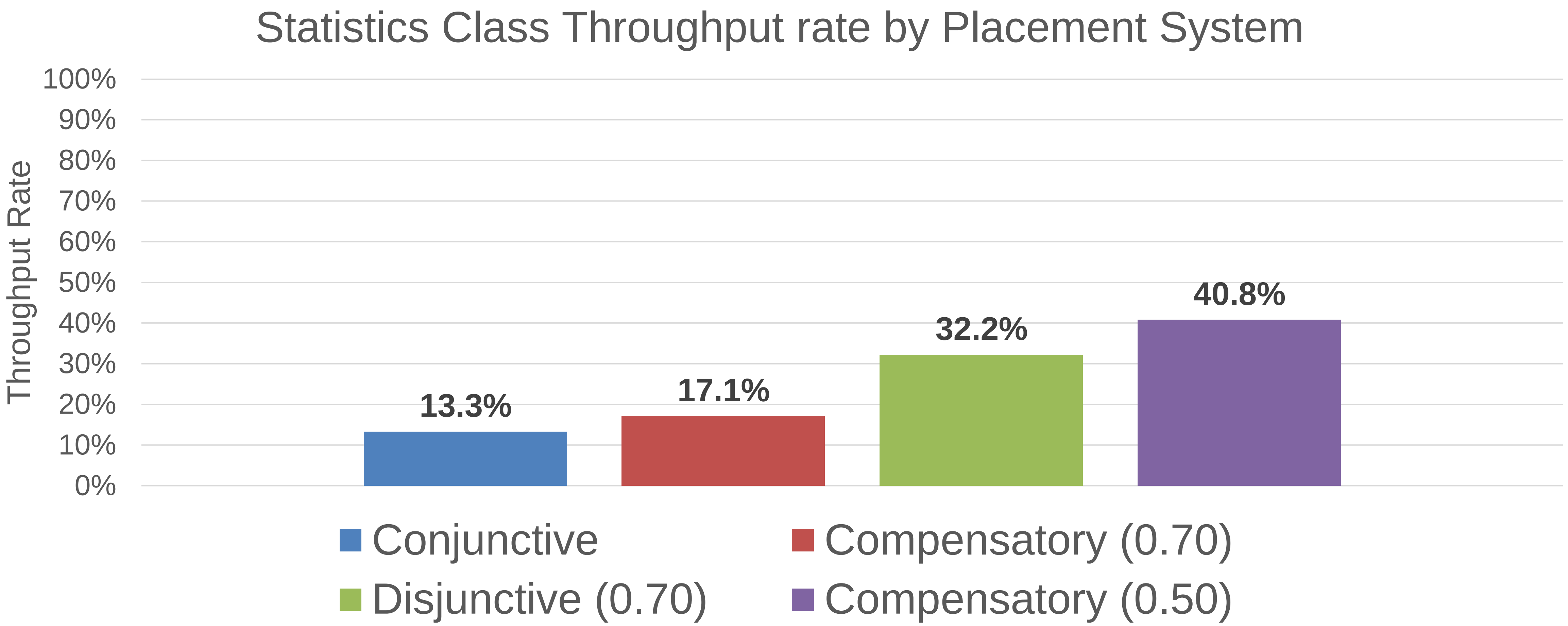
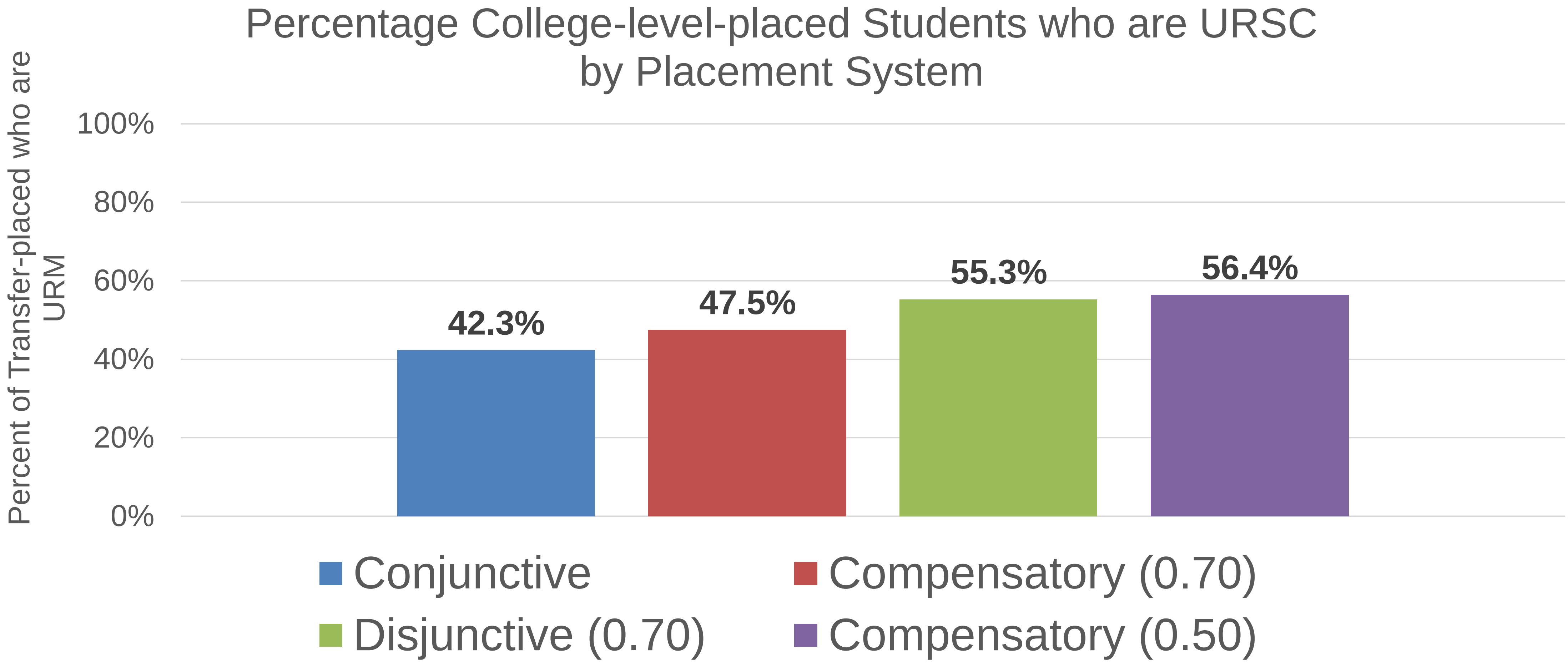
One Year Throughput Rate: College Statistics Course



Percentage of Underrepresented Students of Color College-level Placements



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Summary of Modeling Placement Systems

- No single metric is sufficient but several well-chosen metrics (including throughput) can allow for a more informed decision
- Disjunctive models have higher access and throughput than compensatory models
- The conjunctive model was very restrictive and had the lowest throughput rates and URM placement rates
- Students placed via alternative methods
  - far more likely to be placed into college-level courses
  - successfully complete college-level courses at the same or higher rates when placed there
  - far more likely to complete the gateway course in the discipline
- Students should progress between systems as smoothly as within systems

MMAP Research Team

Terrence Willett
The RP Group
twillett@rpgroup.org

Mallory Newell
The RP Group
newellmallory@deanza.edu

Craig Hayward
The RP Group
chayward@rpgroup.org

Loris Fagioli
The RP Group
lfagioli@ivc.edu

Rachel Baker
UC Irvine
rachelbb@uci.edu

Nathan Pellegrin
The RP Group
nathan.pellegrin@gmail.com

Peter Bahr
University of Michigan
prbahr@umich.edu

John Hetts
Educational Results Partnership
jhetts@edresults.org

Ken Sorey
Educational Results Partnership
ken@edresults.org

Daniel Lamoree
Educational Results Partnership
dlamoree@edresults.org

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