

← **Challenges**

Solutions →

Kara Larkan-Skinner

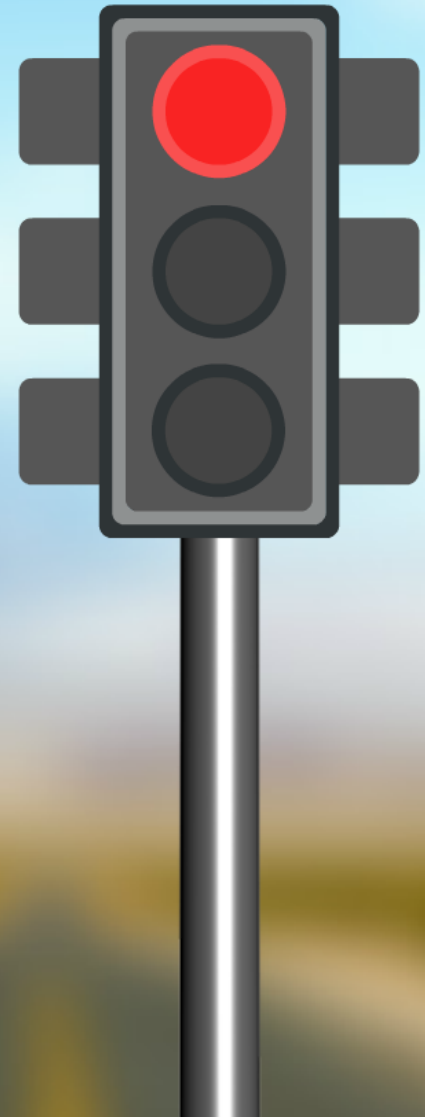
Frances Frey

Using Predictive Models to
Improve Student Success

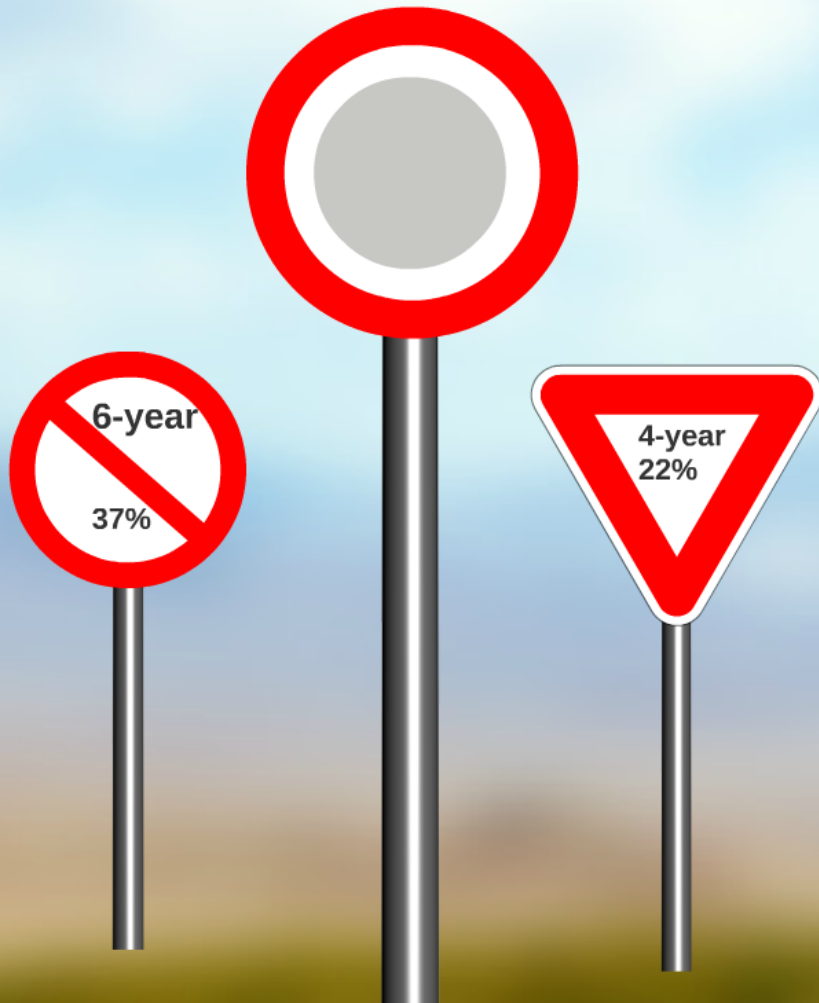
← **Challenges**

Solutions →

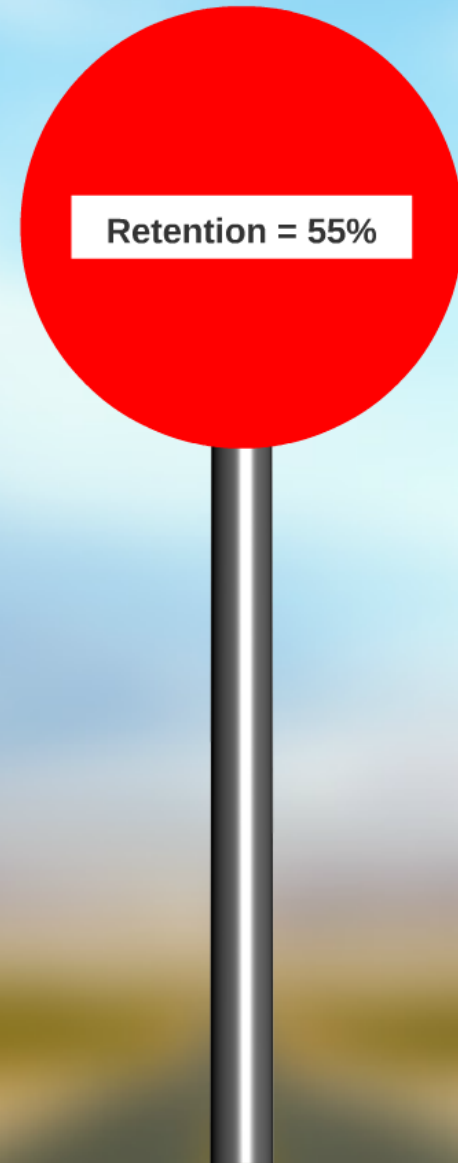
Low Graduation Rates
High Drop/Fail Rates
High Student Debt
High % of At-Risk Students



Low Graduation Rates



Low Fall-to-Fall Retention



High Risk Population



Incoming Student Characteristics

90% of Students At-Risk:

Average SAT = 918

Average ACT = 19

50% First Generation

72% Hispanic

98% on Financial Aid

70% Pell Eligible

35-40%
Losing State Aid
1st Semester
When GPA Drops
Below 2.5





**Need a way to identify
most at-risk students
before they lose aid
and leave.**

← **Challenges**

Solutions →

- Collaboration with Student Success office
- 1st academic year challenges
- Strategic Use of Resources
- Leverage Data to Improve Success
- Use predictive analysis to determine students most at risk before they even step foot on campus

Predicting At-Risk Students

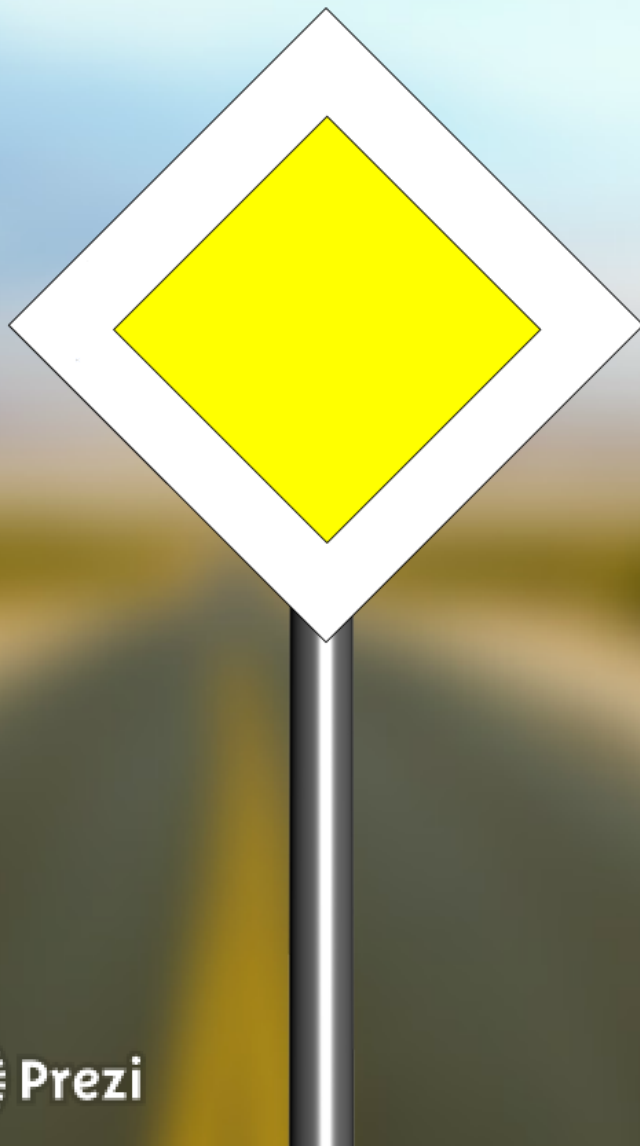
Logistic Regression

- Dichotomous
- Probability score
- Predict group membership
- Aligned with goals

Initial Attempt to Predict Retention

- Unable to predict using pre-entry variables
- First term GPA highly predictive of retention
- Generated new research question





Building Logistic Regression Model

Test Model

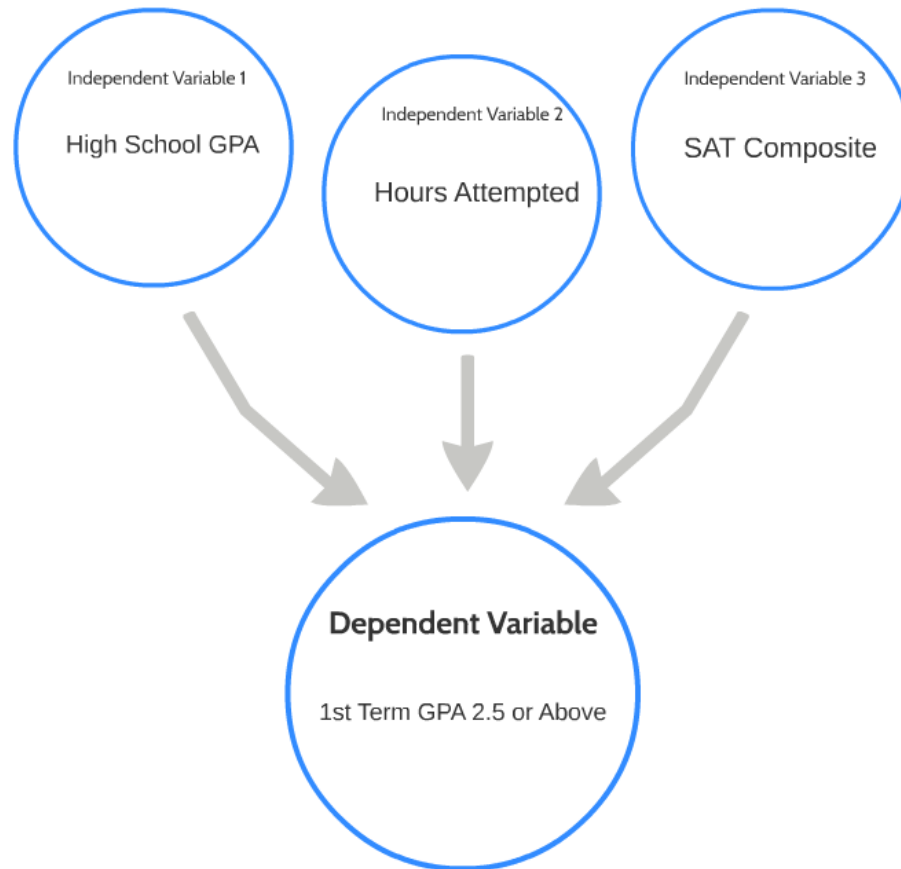
Dependent variable

- 1st Term GPA 2.5 or above (yes or no)

Independent variables

- Financial factors
- High school performance factors
- College entrance exams
- Demographics

Final Model



Model Summary Fall 2012 Data

Model Summary

Step	-2 Log Likelihood	Cox & Snell R Square	Nagelkerke R Square
3	345.488 ^a	.211	.306

Classification Table^a

			Predicted		
			Term GPA >2.499		Percentage Correct
Actual			No	Yes	
Step 3	Term GPA >2.499	No	23	65	35
		Yes	20	253	92
Overall Percentage					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 3 ^c	SAT Comp.	.002	.001	3.904	1	.048	1.002
	HS GPA	1.608	.333	23.316	1	.000	4.993
	Hours Enr.	.366	.071	26.829	1	.000	1.442
	Constant	-11.359	1.586	51.294	1	.000	.000

Results:

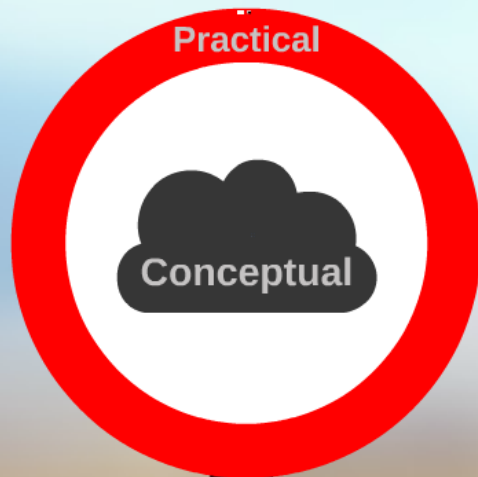
Model = 77% Accurate Fall 2012 Data;

Model = 78% Accurate Fall 2013 Data

Quick Technical Note on Logistic Regression (you can close your eyes and hum for this part)

- With a logistic regression, you are essentially modeling the probability that an individual will fit into one of two groups.
- However, if you use linear regression on a dichotomous variable, you get probabilities > 1 .
- To fix this, the dependent variable is transformed
 - First into odds (odds = $\frac{\text{Probability of Low Risk}}{\text{Probability of High Risk}}$), which makes the range 0 to ∞
 - Then into logits (natural log(odds)), which makes the range $-\infty$ to ∞

OLLU's Model



Created 'Prediction Template':

(Step 1)

$\text{Logit}(\text{probability of Low Risk}) = \text{Constant} + (B * \text{High School GPA}) + (B * \text{Hours}) + (B * \text{SAT})$

(Step 2) Convert logit into odds

(Step 3) Convert odds into probabilities

$\text{Probability} = \text{Odds} / (1 + \text{Odds})$

(Step 4)

Determine your threshold

Reduce number of false positives (i.e., "low risk")

predictive model for retention developed and applied - Microsoft Excel													
O78													
	A	B	F	G	H	I	J	K	L	M	N	O	P
1	ID	Last	Active Reg	SATC	HS GPA	Formula	ExpNum	ExpDen	Probability	Actual Fall Term GPA	Actual Term GPA >=2.5	Predicted Term GPA >=2.5	Model Accuracy
78	SAMPLE					$=-11.359+(1.608*H79)+(0.002*G79)+(0.366*F79)$	$=EXP(I79)$	$=1+J79$	$=J79/K79$				
79	1	Smith	15	1300	4.6		4.1278	62.04128186	63.04128186	98.41%	4	1	1
80	2	Smith	15	1300	4.648		4.204984	67.01952535	68.01952535	98.53%	4	1	1
81	3	Smith	12	1300	4.99		3.65692	38.74183407	39.74183407	97.48%	4	1	1
82	4	Smith	14	1260	4		2.717	15.13484952	16.13484952	93.80%	3.714	1	1
83	5	Smith	13	1230	3.7		1.8086	6.101898791	7.101898791	85.92%	3.769	1	1
84	6	Smith	16	1210	3.8		3.0274	20.64348968	21.64348968	95.38%	3.813	1	1
85	7	Smith	14	1190	3.6		1.9338	6.915740186	7.915740186	87.37%	0.214	0	0
86	8	Smith	15	1160	3.69		2.38452	10.85385157	11.85385157	91.56%	3.8	1	1
87	9	Smith	12	1150	3.56		1.05748	2.879106491	3.879106491	74.22%	2.333	0	0
88	10	Smith	13	1140	3.2		0.8246	2.280968196	3.280968196	69.52%	3.308	1	1
89	11	Smith	13	1140	3.9		1.9502	7.030093459	8.030093459	87.55%	3.692	1	1
90	12	Smith	13	1140	3.296		0.978968	2.661707941	3.661707941	72.69%	1.846	0	0
92	14	Smith	15	1130	4		2.823	16.8272568	17.8272568	94.39%	3.8	1	1
93	15	Smith	13	1130	3		0.483	1.620929905	2.620929905	61.85%	3.538	1	1
94	16	Smith	13	1110	3.5		1.247	3.479887619	4.479887619	77.68%	2.308	0	0
95	17	Smith	14	1100	3.7		1.9146	6.784224564	7.784224564	87.15%	4	1	1
96	18	Smith	18	1100	2.7		1.7706	5.87437693	6.87437693	85.45%	3	1	1
97	19	Smith	14	1090	3.09		0.91372	2.493581424	3.493581424	71.38%	3.357	1	1
98	20	Smith	13	1090	2.33		-0.67436	0.509482385	1.509482385	33.75%	0.923	0	0
99	21	Smith	18	1080	3.6		3.1778	23.99390884	24.99390884	96.00%	4	1	1
100	22	Smith	14	1080	2.471		1.506268	4.510210520	5.510210520	81.95%	4	1	1

	A	B	C	D
1	Retention Alert Model			
6	Predictive GPA Model			
7	HSGPA	3.06		
8	SAT	850		
9	First Sem Reg Hrs	12		
10				
16	Probability > 2.5		69.86%	
17				
18				
19				
20				

End User View

Organizational Impact

- Enrollment Management
- Student Success Division
- 3rd Party Vendor



Results

- 10% increase in 2.5+ GPA
- Fall-Fall retention increased 8%
- Estimated \$500,000 - \$1M savings
- 77-78% model accuracy

Next Steps

Monitor Model

- Long-term impact
- Triage effectiveness

Other Predictions

- Online courses
- Enrollment

Advocate for Policy Change

- Financial aid
- Advising

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