

Predictive Analytics Work Group

University of Hawai'i System

Meeting #1
April 28, 2017

- Welcome, introductions
- Review purpose of group and member roles.
- Share an example of an enrollment yield prediction model.
 - Provide a conceptual understanding of how a predictive model for enrollment works
 - Look at a successful case study (UT Austin) and relevant research (Goenner & Pauls, 2006)
 - Present findings from a UH prediction analysis.
 - Discuss possible uses of prediction data.
- Next Steps
- Wrap up

OPENING ENROLLMENT

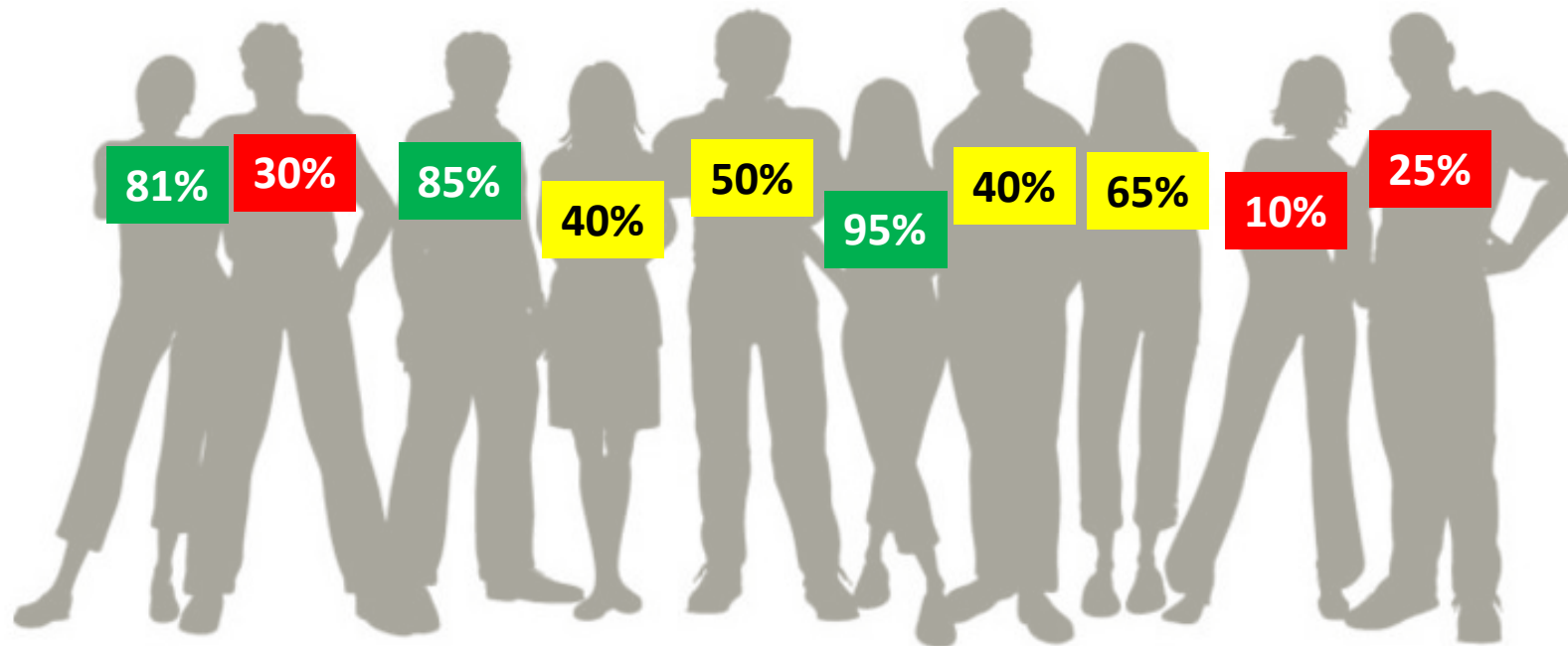
115 days before the first day of instruction.

	Fall 2017	%C	Fall 2016	%C	Fall 2015	%C	Fall 2014	%C	Fall 2013
UH	20,761	-8.9	22,797	-5.8	24,192	-2.7	24,860	-17.2	30,021
Mānoa	7,680	-4.5	8,041	-6.7	8,623	-5.3	9,101	-14.6	10,656
Hilo	1,822	-13.5	2,107	-10.4	2,352	28.3	1,833	-25.7	2,467
West O'ahu	1,433	-11.2	1,614	7.7	1,498	9.8	1,364	14.8	1,188
UHCC	9,826	-11.0	11,035	-5.8	11,719	-6.7	12,562	-20.0	15,710
Hawai'i Community College	870	-11.4	982	0.0	982	-17.9	1,196	-23.5	1,564
Honolulu Community College	1,194	-15.4	1,411	-5.9	1,499	-14.6	1,755	-19.5	2,181
Kapi'olani Community College	2,963	-11.6	3,353	-6.2	3,573	-2.9	3,681	-18.7	4,530
Kaua'i Community College	361	-10.4	403	-3.1	416	-15.1	490	-14.6	574
Leeward Community College	2,637	-7.5	2,851	-5.9	3,031	-0.6	3,049	-18.1	3,725
Maui College	1,070	-11.1	1,204	-14.9	1,414	-13.1	1,627	-21.5	2,072
Windward Community College	731	-12.0	831	3.4	804	5.2	764	-28.2	1,064

April 28, 2017

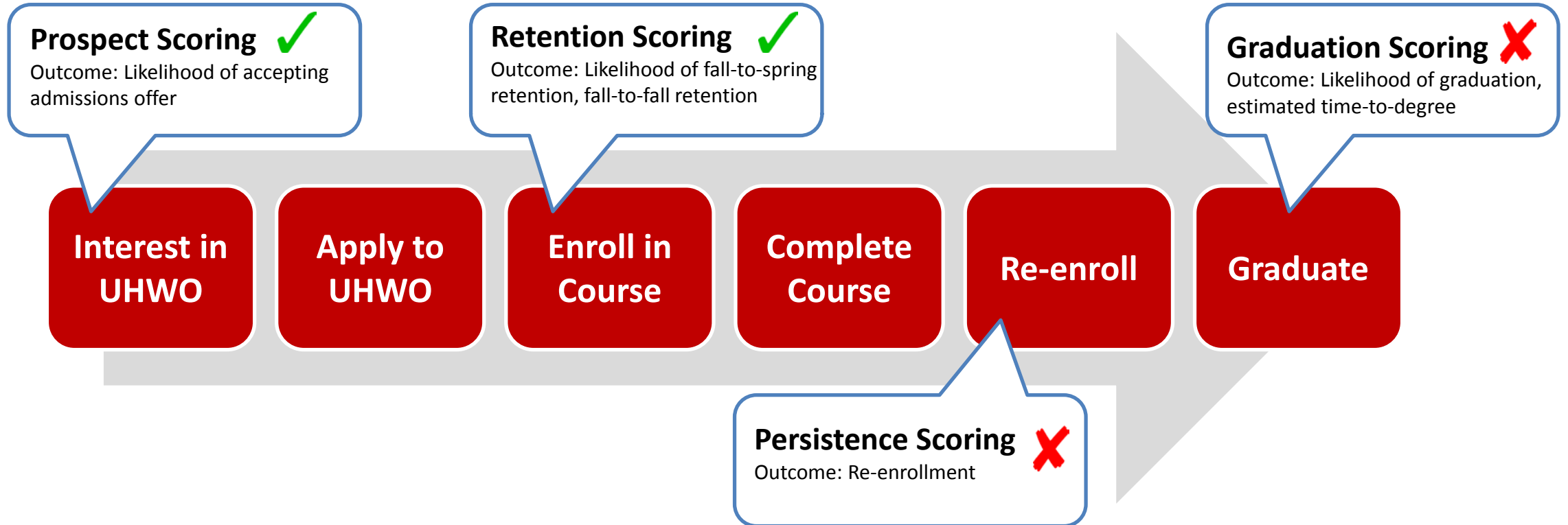
- Explore/test emerging ideas around predictive modeling and data visualization in areas of enrollment management and student success.
- Strategies may eventually be used by the System Office and the campuses.
- Your role:
 - Attend a few meetings over the summer
 - Provide input
 - Contribute in development

- Uses historical data to predict or forecast future behaviors, trends, or outcomes.
(i.e. enrollment likelihood, retention, course success, degree completion/time-to-degree, etc.)



- Admissions recruitment
 - Predict which students are likely to enroll at your institution (Goenner & Pauls, 2006)
- Identifying at-risk students
 - Predict which students are likely to drop out or fall behind academically. (Herzog, 2006 ; Sujitparapitaya, 2006)
- Students' price responsiveness to tuition increases or financial aid incentives (Des Jardins, 2001; Herzog & Stanley, 2017)

Predictive analytics for the enrollment funnel



Many colleges using predictive analytics



University of Nevada, Reno



Georgia State
University



Missouri
State

UC San Diego



UNIVERSITY
of HAWAI'I[®]
WEST O'AHU

SJSU SAN JOSÉ STATE
UNIVERSITY



ARIZONA STATE UNIVERSITY



TEXAS
The University of Texas at Austin

UC DAVIS
UNIVERSITY OF CALIFORNIA



Virginia Tech

For the Class of 2017:

- 94.6 percent retention, up from 93.6 percent prior year, resulting in the highest rate in the university's history.
- Average GPA of 3.28, up from 3.22 for previous cohort.
- Students enrolled in and passed more SSH (average 13.32 hours passed) than any entering class in the past five years.

Predictive Modeling



Data Informs Every Decision

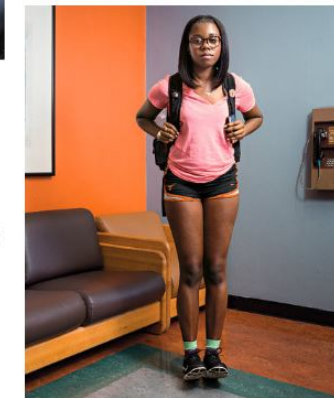
With more than 35,000 applicants to The University of Texas at Austin last year, it is critical we make data-informed decisions to ensure the enrollment of a high-quality class that has the resolve to graduate in four years.

David Laude, "Graduation Czar"



The New York Times Who Gets to Graduate?

By PAUL TOUGH MAY 15, 2014

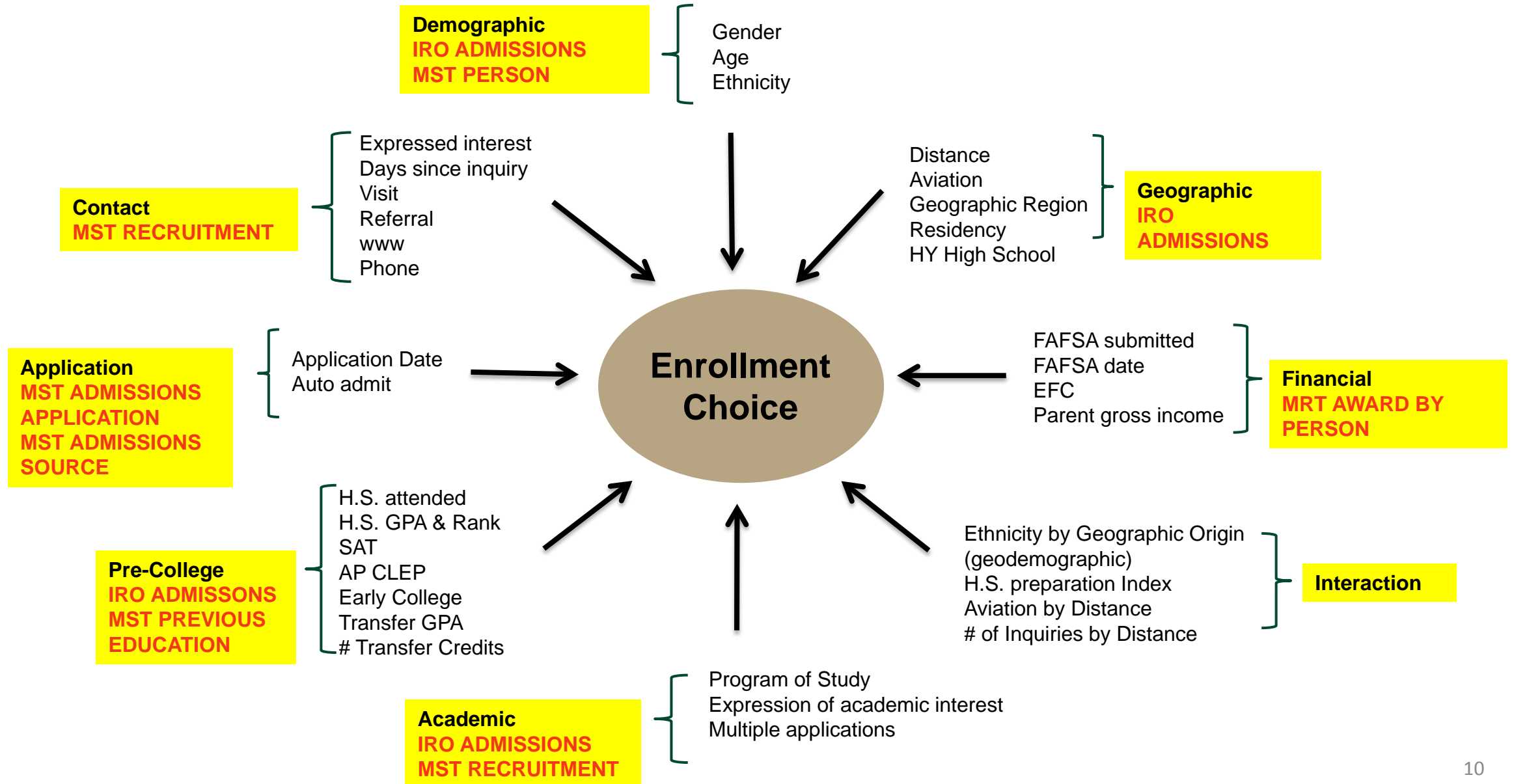


For as long as she could remember, Vanessa Brewer had her mind set on going to college. The image of herself as college student appealed to her — independent, intelligent, a young woman full of potential — but it was more than that; it was a chance to rewrite the end to a family story that went off track 18 years earlier, when Vanessa's mother, then a high-achieving high-school senior in a small town in Arkansas, became pregnant with Vanessa.

Vanessa's mom did better than most teenage mothers. She married her high-

Vanessa Brewer Bill McCullough for The New York Times

SIS data avail. for enrollment prediction



- Identify 'fence sitter' freshmen accepts at peak recruitment season (~March 15)
- Develop regression model to predict enrollment likelihood of future cohort
 - Determine baseline enrollment yield to maximize correct classification
 - Identify statistical outliers to get trimmed dataset
 - Choose parsimonious model with optimal balance in correct classification
- Dropout risk scoring for new freshmen
 - Transformation of the $\text{logit}(p)$ into probability scores
 - Automated classification and probability score with SPSS
 - Decile grouping of scored students
- Reporting of enrollment likelihood via secure online access

- Data sources
 - Matriculation system (Banner ODS)
- Student cohorts
 - New first-time freshmen accepts (UHM)
 - Fall entry 12', 13', 14', 15' for model dev. (training set, N=23,532)
 - Fall entry 2016 for model validation (holdout set, N=6,252)
- Data elements at March 15
 - Contact: expressed interest, number of applications
 - Geographic: distance, residency, high yield geog region, high yield high school
 - Geodemographic: geog. region by ethnicity, gender, SES
 - Academic: program of study
 - Timing: date of application days/weeks until semester start
 - Financial: FAFSA submitted

- Exploratory data analysis
 - Variable selection (bivariate correlation on outcome variable)
 - Variable coding (continuous vs. dummy/binary)
 - Missing data imputation
 - Derived variable(s)
 - $HSPrep = (HSGPA * 12.5) + (ACTM * .69) + (ACTE * .69)$ (not used today)
- Logistic regression model
 - Preliminary model fit (-2LL test/score, pseudo R2, HL sig.)
 - Check for outliers with diagnostic tools (Std residuals, Cook's)
 - Check for collinearity (VIF)
 - Check correct classification rate (CCR) for enrollees vs. non-enrollees (i.e. model sensitivity vs. specificity) using baseline probability and Receiver Operating Characteristics (ROC) curve

Predictive model derived from ODS data

		Variables in the Equation				
		B	S.E.	Wald	Sig.	Exp(B)
Step 1 ^a	Constant	-3.782	0.124	923.359	0.000	0.023
	Resident	2.734	0.108	637.039	0.000	15.394
	Historically high yield Hawaii HS	0.822	0.042	392.014	0.000	2.275
	Expressed interest	0.570	0.033	307.384	0.000	1.768
	Parent gross income less than 85k	0.477	0.033	210.283	0.000	1.611
	Female	-0.286	0.032	77.451	0.000	0.751
	Low yield US region	0.957	0.118	66.176	0.000	2.604
	CTAHR SOEST applicant	-0.655	0.082	63.061	0.000	0.520
	Nor Cal	-0.278	0.045	37.718	0.000	0.757
	High yield Isle region	0.299	0.054	31.075	0.000	1.348
	Application date 270 days or older	-0.189	0.038	25.005	0.000	0.828
	Number of applications	0.150	0.040	13.980	0.000	1.161
	Miles from campus over 20	-0.137	0.042	10.438	0.001	0.872

Pseudo Rsquare = .263

Classification accuracy

Classification Table^a

Observed			Predicted					
			Training Dataset			Holdout Dataset		
			ENROLLED		Percentage Correct	ENROLLED		Percentage Correct
			No	Yes		No	Yes	
Step 1	ENROLLED	No	13238	2567	83.8	3517	784	81.8
		Yes	3816	3304	46.4	908	921	50.4
	Overall Percentage				72.			72.4

a. The cut value is .432

- Scoring of relative dropout/retention risk

$$p = \frac{\exp(a + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 + \dots)}{1 + \exp(a + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 + \dots)}$$

Where: p = probability of enrollment/non-enrollment
 exp = base of natural logarithms (~ 2.72)
 a = constant/intercept of the equation
 b = coefficient of predictors (parameter estimates)

Sample data for admissions/recruitment

Customer Relationship Management System

Decile High School Code Desc Student ID

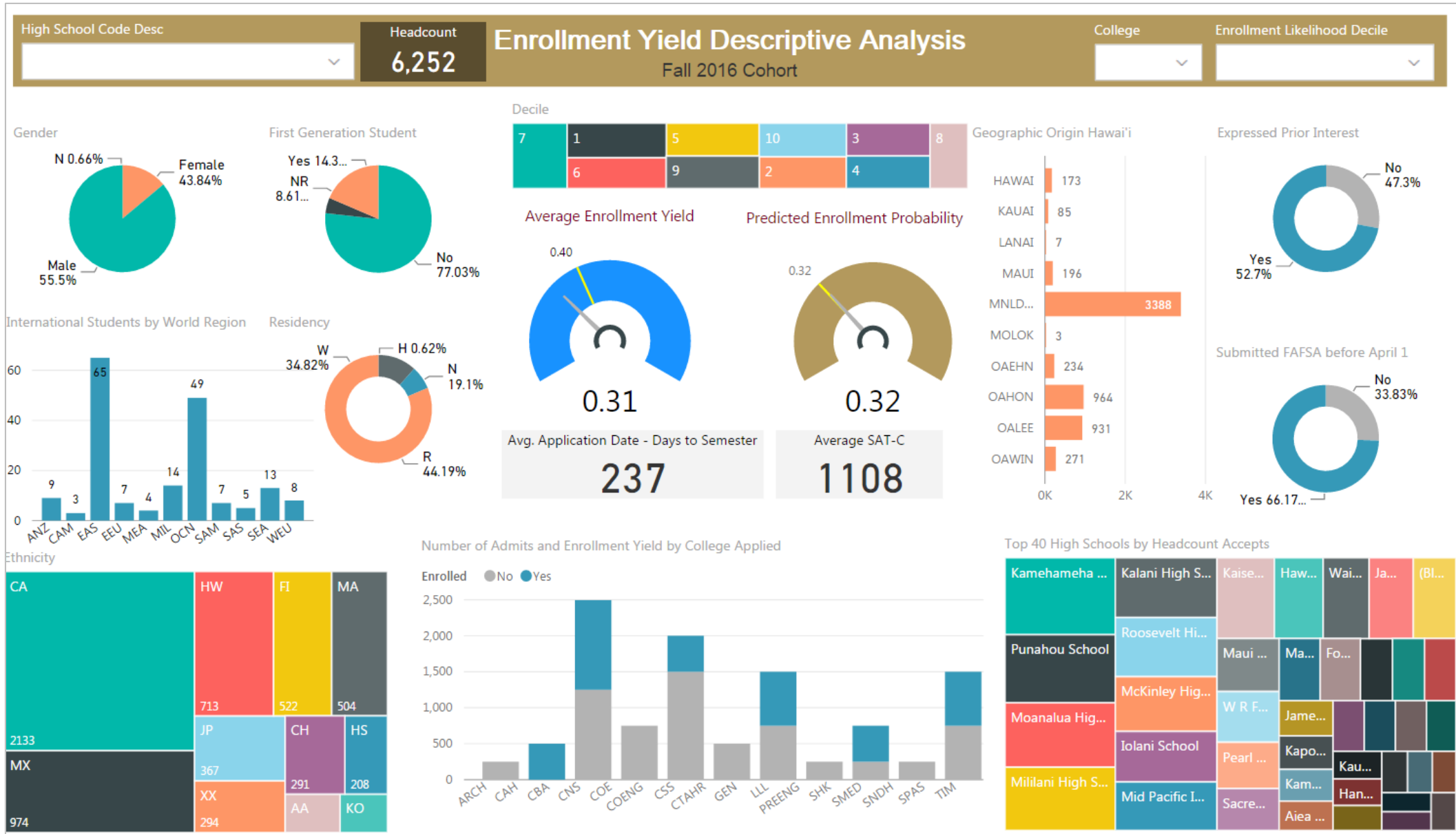
Decile	Predict...	Student ID	Student Name	Student Email	Student Phone	Applicatio...	City	State	Expressed Prior Int...	FAFSADate	Missing HS Tran...	Ge...	Ge...	Ge...	High S...	College
10	0.02	412023443	Student Name 100	example@hawaii.edu	808-123-4567	1/4/2016 1...	VE...	CA	Yes	Tuesday, January 26, 2016	Yes	WST	M...	MN...		SNDH
10	0.03	743002674	Student Name 1031	example@hawaii.edu	808-123-4567	12/4/2015 ...	W...	HI	Yes		Yes	WST	OA...	WA...		COENG
10	0.03	563464225	Student Name 1091	example@hawaii.edu	808-123-4567	9/16/2015 ...	W...	NJ	No	Friday, January 01, 2016	Yes	NET	M...	MN...		CNS
10	0.04	530616078	Student Name 1093	example@hawaii.edu	808-123-4567	12/21/201...	PO...	GA	No		Yes	SOU	M...	MN...		COE
10	0.04	199379718	Student Name 1107	example@hawaii.edu	808-123-4567	2/1/2016 8...	BU...	CA	Yes	Saturday, January 30, 2016	Yes	WST	M...	MN...		GEN
10	0.03	732665957	Student Name 1171	example@hawaii.edu	808-123-4567	11/30/201...	BE...	TX	Yes		Yes		M...	MN...		CSS
10	0.03	194975691	Student Name 1200	example@hawaii.edu	808-123-4567	9/21/2015 ...	GR...	MI	Yes	Sunday, February 14, 2016	Yes	M...	M...	MN...		CTAHR
10	0.02	358474970	Student Name 1212	example@hawaii.edu	808-123-4567	1/22/2016 ...	VA...	WA	Yes		Yes	NWT	M...	MN...		GEN
10	0.02	290108797	Student Name 1242	example@hawaii.edu	808-123-4567	10/5/2015 ...	EL ...	CA	Yes		Yes	WST	M...	MN...		SNDH
10	0.03	145441005	Student Name 1259	example@hawaii.edu	808-123-4567	4/19/2016 ...	E...	HI	Yes	Sunday, February 07, 2016	Yes	WST	OA...	EWA		SNDH
10	0.04	234889977	Student Name 1294	example@hawaii.edu	808-123-4567	9/28/2015 ...	RO...	GA	No		No	SOU	M...	MN...	312	GEN
10	0.01	696966423	Student Name 1344	example@hawaii.edu	808-123-4567	11/19/201...	BE...	CA	No	Monday, January 11, 2016	Yes	WST	M...	MN...		GEN
10	0.03	903629305	Student Name 1354	example@hawaii.edu	808-123-4567	9/4/2015 7...	GR...	MI	No	Friday, January 01, 2016	No	M...	M...	MN...	500	CNS
10	0.02	282191613	Student Name 1382	example@hawaii.edu	808-123-4567	11/30/201...	SA...	CA	Yes		Yes	WST	M...	MN...		SNDH
10	0.04	121533330	Student Name 1388	example@hawaii.edu	808-123-4567	3/1/2016 9...	CA...	CA	Yes	Saturday, February 27, 20...	Yes	WST	M...	MN...		SNDH
10	0.03	919831116	Student Name 1392	example@hawaii.edu	808-123-4567	1/15/2016 ...	LI...	HI	Yes	Tuesday, January 12, 2016	Yes	WST	KA...	LIH...		SNDH
10	0.04	680581088	Student Name 1521	example@hawaii.edu	808-123-4567	10/20/201...	H...	HI	Yes		Yes	WST	OA...	HO...		TIM
10	0.03	265355751	Student Name 1530	example@hawaii.edu	808-123-4567	10/26/201...	RI...	TX	Yes	Sunday, January 03, 2016	Yes	SOU	M...	MN...		CTAHR
10	0.02	200177881	Student Name 1565	example@hawaii.edu	808-123-4567	10/7/2015 ...	KI...	HI	No	Sunday, January 31, 2016	No	WST	M...	KIHEI		SNDH
10	0.04	987144673	Student Name 1589	example@hawaii.edu	808-123-4567	10/15/201...	H...	HI	Yes		No		M...	MN...		GEN
10	0.03	178551254	Student Name 1624	example@hawaii.edu	808-123-4567	12/17/201...	DE...	CO	Yes		Yes	WST	M...	MN...		LLL
10	0.02	752815968	Student Name 1653	example@hawaii.edu	808-123-4567	11/5/2015 ...	SA...	CA	Yes		Yes	WST	M...	MN...		SNDH
10	0.04	217603131	Student Name 1661	example@hawaii.edu	808-123-4567				Yes		Yes		M...	MN...		CNS
10	0.03	685546233	Student Name 1714	example@hawaii.edu	808-123-4567	12/10/201...	M...	SC	Yes	Monday, January 18, 2016	Yes	SOU	M...	MN...		SNDH
10	0.03	248633498	Student Name 172	example@hawaii.edu	808-123-4567	11/16/201...	GR...	IL	Yes		Yes	M...	M...	MN...		SNDH
10	0.03	577342296	Student Name 173	example@hawaii.edu	808-123-4567	10/8/2015 ...	KA...	HI	Yes	Sunday, January 17, 2016	No	WST	OA...	KAL...		SNDH
10	0.04	312413553	Student Name 1777	example@hawaii.edu	808-123-4567	12/31/201...			Yes		Yes		M...	MN...		CNS
10	0.03	704246993	Student Name 1781	example@hawaii.edu	808-123-4567	12/1/2015 ...	LA ...	CA	Yes	Tuesday, January 05, 2016	Yes	WST	M...	MN...		SNDH
10	0.02	245851083	Student Name 1784	example@hawaii.edu	808-123-4567	11/23/201...	TE...	CA	Yes		Yes	WST	M...	MN...		SNDH
10	0.03	997566997	Student Name 179	example@hawaii.edu	808-123-4567	9/30/2015 ...	TI...	IL	Yes	Monday, February 15, 2016	No	M...	M...	MN...		SNDH
10	0.02	695469021	Student Name 1793	example@hawaii.edu	808-123-4567	10/14/201...	JA...	WY	Yes		Yes	NWT	M...	MN...		SNDH
10	0.04	356676895	Student Name 1832	example@hawaii.edu	808-123-4567	11/30/201...	LO...	CA	Yes	Tuesday, March 01, 2016	Yes		M...	MN...		COE
10	0.04	249979384	Student Name 1859	example@hawaii.edu	808-123-4567	1/4/2016 8...	LA...	UT	Yes		Yes	WST	M...	MN...		SNDH
10	0.04	876713618	Student Name 1904	example@hawaii.edu	808-123-4567		GA...	FL	No		Yes	SOU	M...	MN...		GEN
10	0.03	998792934	Student Name 1907	example@hawaii.edu	808-123-4567	11/6/2015 ...	FIS...	IN	Yes	Monday, May 30, 2016	No	M...	M...	MN...		SNDH
10	0.02	748857638	Student Name 1935	example@hawaii.edu	808-123-4567		PE...	HI	No		Yes	WST	OA...	PE...		SMED
10	0.01	886255218	Student Name 1981	example@hawaii.edu	808-123-4567	12/1/201...	M...	CA	Yes	Monday, February 29, 2016	Yes	WST	M...	MN...		CNS
Total															508998	

Tile reports for enrollment mgt. support



Dashboard tiles organized to ascend reports from descriptive to predictive modes.

Descriptive analysis by prediction deciles

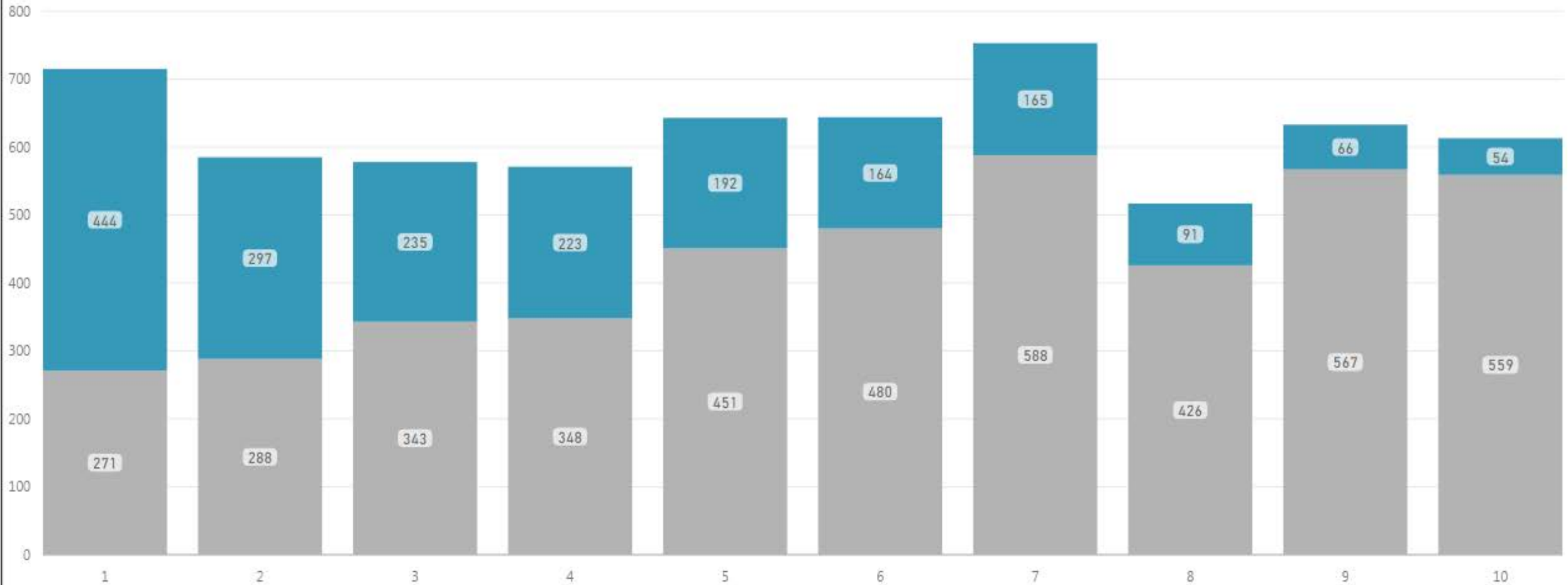


Deciles

[Back to Report](#)

ENROLLMENT LIKELIHOOD DECILE BY ACTUAL ENROLLMENT OUTCOME (1=HIGH LIKELI..

Enrolled ● No ● Yes



Questions?

Predictive Analytics Work Group

- John Stanley (Co-Chair, UH West Oahu)
- Pearl Iboshi (Co-Chair, UH System)
- David Mongold (UH System)
- Eric Wen (UH West Oahu)
- Jared Takazawa (UH System)
- Jim Cromwell (UH West Oahu)
- Karen Lee (UH CC System)
- Kelli Okumura (UH Hilo)
- Nicholas Todd (UH System)
- Roy Suda (UH Manoa)
- Ryan Yamaguchi (UH Manoa)
- Sheryle Proper (UH System)
- Wilson Lau (UH CC System)
- Zach Street (UH Hilo)