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SAS PROC REPORT: How It Helps Improving College Student Retention Rate

Harjanto Djunaidi and Monica Djunaidi[1]

Abstract

This paper has shown how SAS PROC REPORT combined with other SAS PROCs can be utilized and applied by US colleges to improve their student retention and graduation rate. These education analytics approaches and tools are becoming more important after the Administration recently announced that College Affordability Rating (CAR) criteria will be used as the basis in awarding federal funding such as Pell grant to US Colleges. Higher learning institutions with higher CAR will be awarded more federal money compared to those who have lower rating. Time is running out for the colleges to improve their report card such as graduation rate which is one of the components measured in the CAR. These institutions have practically one academic year not only to improve the graduation rate, but also to reduce their tuition and their students' debt. Therefore, the ability to produce various reports and analyses timely that meet the decision makers' needs are important and no longer an option, but a must. Strategic decisions have to be made constantly, and they need to be supported by accurate data, professionally analyzed, provided and presented in a timely basis. Applying statistical approaches such as multivariate analyses, an Institutional Research Intelligence (IRI) expert is able to identify the odds of freshmen-year students to drop-out from their program. These estimation results combined with the output generated by PROC REPORT will help to group high risk student population so that appropriate policy and early intervention efforts can be done to minimize the possible damages. This new early alert approach applied to identify high risk students is increasingly vital in a more volatile education industry. It is even more vital, after the CAR regulation was announced. Except for the top-tier schools, most US colleges, either at a two-year or four-year public or private, not-for-profit or for-profit institutions are struggling to keep both under-prepared full-time and part-time, first-time students to survive their freshmen year courses. Therefore, they are more likely will face serious challenges to improve their graduation rate which in turns will reduce their ability to get funding from the federal government.

[1] **Founder and co-founder, the Association of American Education Analytics (http://www.AAEA.us). Authors of the first education analytics book in the market (Institutional Research Intelligence: Go beyond Reporting). Innovator of Institutional Research Intelligence paradigms and Chief Editor, American Journal of Education Analytics. Contact: harry.djunaidi@IRIntelligence.org.**

Introduction

Improving the rate of student retention and graduation rate is becoming more important than what it was in the past. On average, student retention rates in most US colleges are between 30 to 60 percent while the graduation rate is much lower. AAEA has recently completed research on CAR and the results show that on average, the graduation rate in the state of Alaska is 29.43% while it is 67.79% in Rhode Island[2].

Sixty eight percent graduation rates indicate that about 32 % of full-time first-time students will drop either after the first semester or after the first year. The drop-out rates are usually higher for part-time students. The research results also show that the rates of survival at the Ivy League colleges are much higher and above 90 percent. When students drop out from their programs, unnecessary new debts have also been created through the student loans borrowing. This study may not relevant for top tier schools, but very important for average US colleges which are facing the retention problem and have tried hard using conventional ways in the past to improve their retention and graduation report card.

There are many factors which must have affected the freshmen-year college student retention rates. Factors such as students' readiness for college classes (academic credentials), the amount of financial aid awards and the rigor of the freshmen year courses could have significant impacts when they make their decision either to stay or leave the programs or to transfer out institutions. Among these important factors, several variables of college readiness or students' academic credentials can be used. Past studies (Djunaidi, 2012) have shown that assessment scores such as ACT composite or SAT scores are good predictors of college student drop-out in addition to high school GPA.

[2] Complete results are available on the following book: College Affordability Rating: Strategy to Increase Federal Financial Aid, Academy Data Analytics Publisher, First Edition 2013 (http://www.aaea.us/recent-education-policy-changes/).

Steps to Estimate the Model

There are simple steps that an institution can do to identify high risk student population. The first step is to identify factors that affect the retention rate by estimating a PROC FACTOR to identify various possible elements or characteristics which are hypothesized to affect the rate. The following SAS programs and codes are useful:

```
Data Retention; Set IRI_Data;
PROC FACTOR data=Retention
method=ml N=5 ROTATE=VARIMAX scree;
VAR R_rate HSGPA ACT_COMP Others;
run;
```

These SAS Codes generate results which can be used to identify a group of variables or factors which might have positive or negative impacts on the students' retention rate. Past studies have found that high school GPA and assessment tests such as ACT or SAT composite scores are good explanatory variables. If the data are available, one may need to explore and use the sub-scores instead of the composite score as the predictors. Other variables which may have impacts on the drop-out rate is the amount of financial awards such as Perkins Loans, Pell Grant, Stafford Loans as well as other institutional and state financial aids or scholarships awards. Suppose that after running the PROC FACTOR, only two variables are significant and they can be grouped into one trait, namely student credentials as measured by ACT composite score and high school GPA.

The next step that one can do is to look at the school's drop-out historical data. In this paper, they are assumed to have been pulled and are saved in the **IRI_Data** file. The longer the period of past information covered in the analyses, the better the IRI expert can examine and find out the common and salient information from the drop-out students' population data. Past studies found that lower high school GPA and assessment scores will increase the likelihood of students to drop-out. It makes a perfect sense that high school GPA is the best predictor of students' ability to take college level courses, assuming the grades are normally distributed and that they are real and un-inflated[3]. The assessment test scores are the second check which may confirm the freshmen year college students' readiness to take college level courses. This is the reason why multivariate statistical analyses need to be estimated before deciding which variables are the best predictors of drop-out rate.

The second step that an education analytics or a data scientist can do after finding the salient factors is to make the cut-off and then translate the policy or rules into SAS Codes. Suppose that the information from step one indicates that these two variables are indeed the good predictors of student success. To show the example of this approach, we have made the data (**IRI_Data**) available and they can be accessed through the following link: http://www.aaea.us/sas-codes-programs/. Once you are in the website, click on **AAEA_Data**.

If the Senior Leadership Team members have agreed on the Institutional Research Intelligence Office (**IRIO**) findings in that the majority of drop-out students are those who have an ACT composite score less than 20 and less than 3.0 high school cumulative GPA. Therefore, the following SAS codes can be written to make a smaller data set which only contains students that satisfy these conditions:

```
Data DO_Potential; Set IRI_F2013;
If (ACT_Comp < 20 and HSGPA < 3);
Run;
```

Please keep in mind that the **IRI_F2013** data file contains information for the 2013 fall semester or incoming students. Flagging those students who may not be able to pass their first 2013 fall semester is very crucial. This valuable information enables the Office of Student Success (OSS) to work with those flagged student to determine: (1) Any additional and necessary preparations need to be done; (2). Type of courses that need to be taken before the first day of fall semester begins. Though it looks simple, this action may have significant impacts to avoid more and serious financial trouble later. To name an example of possible trouble is the new FAFSA 2013 rule which may restrict and deny paying tuition for students who retake

[3]Several schools have been advised to only apply high school GPA as a predictor in their retention model. The question then comes down to the C-statistics. If only use one explanatory variable and the model is able to classify 90% or better of the population correctly, then it certainly a fantastic piece of research. Otherwise, AAEA would suggest for schools to check what is the C-value of their produced early alerts model?

the same courses which he or she has previously taken. This new rule is another example of regulator's recent policy changes that need and can be accommodated into the SAS codes. Point-and-click other than SAS statistical software may be less relevant in today's competitive, uncertain and more volatile education industry.

After the second step, the data scientist can apply the PROC REPORT SAS codes as shown below to identify the group of risky students. These codes will help generating the strategic information to guide college administrators to make strategic decisions regarding student retention. The results of running these codes are shown in Appendix-1:

```
PROC REPORT
DATA=Incoming_F2013(OBS=MAX) NOWD
HEADLINE;
COLUMN '-Students Information-'
StudentID HS_State HS_Name)
('-Programs or Majors-'
Program_Code)('-Credentials-'
HSGPA ACT_COMP Prob);
COMPUTE Prob;
IF (_C5_ < 3 and _C6_ < 20)  THEN
CALL DEFINE("_C7_", "style",
"STYLE=[BACKGROUND=lightRED]");
ENDCOMP;
DEFINE Program_Code/GROUP WIDTH=24;
DEFINE StudentID/GROUP WIDTH=24;
DEFINE HS_State/GROUP WIDTH=24;
DEFINE HS_Name/GROUP WIDTH=24;
DEFINE HSGPA/GROUP "High School
GPA" WIDTH=24;
DEFINE ACT_COMP/GROUP "COMP ACT
SCORE" WIDTH=34 FORMAT=26.2;
DEFINE Prob/"Dropped-Out-Flag"
WIDTH=24;
RUN;
```

One can do a more rigorous study than what has been discussed above. For example, the **IRIO** can calculate the probability of drop-out using a logistic model. This approach has been discussed by Djunaidi in 2012 SCSUG meeting in Houston. Therefore, it will not be repeated here. The entire research manuscript can be accessed through the following link: http://www.scsug.org/wp-content/uploads/2012/11/SCSUG_Enrollment-Paper.pdf or through the Association website. If the logistic model is estimated, the risks of freshmen year students to possibly drop-out can be identified easily by the PROC REPORT. One can run the same codes with minor changes to flag students who may not be able to make it. Perhaps, the logistic risk modeling is a more rigorous approach and therefore, is preferred to be applied. Regardless of the approaches, the finding should show consistent results for both studies are based on the same predictor variables.

Let us take a further look at the students' academic credentials of the group who are not going to make it. What are they characteristics, what are their academic credentials that cause them not to make it? This research question can be answered by looking closely in the `Data DO_Potential` file. The **IRIO** can use PROC FREQ to analyze the drop-out student population by applying the following SAS codes:

```
Data La; Set AAEA.AAEA_DATA;
If (ACT_Comp < 20 and HSGPA < 3);
Run;
Proc Sort data=La Out=La_Out; By
StudentID;
Run;
Proc Freq data=La_Out;
Table (HS_State)*(Age Gender
Ethnic)/Nocol Norow Nopercent;
Run;
```

The codes produce the following results:

Table 1 - Drop-out Students Profile by State and Age

State / Age	16	18	19	20	21	23	Total
AR	0	1	0	1	0	1	3
MS	0	0	0	0	1	0	1
OK	0	0	1	0	0	1	2
TX	1	1	3	2	0	1	8
Total	1	2	4	3	1	3	14

Table 2 - Drop-out Student Profile by State and Gender

State / Gender	F	M	Total
AR	1	2	3
MS	0	1	1
OK	0	2	2
TX	2	6	8
Total	3	11	14

Table 3 - Drop-out Student Profile by State and Ethnicity

State / Ethnic	A	B	H	W	Total
AR	0	1	2	0	3
MS	1	0	0	0	1
OK	0	0	0	2	2
TX	2	2	2	2	8
Total	3	3	4	4	14

The above information gives valuable information to the EAO (Enrollment & Admissions Office) of whom they need to recruit in the future. Needless to say that the interests of these two offices (EAO and OSS) may not always be coincide. We have seen in many colleges that EAO's objective is to fill the seats. In the process, this office may have compromise the quality of recruited students so long they achieved the target enrollment numbers. However, EAO's policy has direct impacts on the OSS's ability to keep the students around. These two seemingly different goals often lead to difficult work relation between these two offices. Perhaps, colleges may need to apply AQIP (Academy Quality Improvement Project) or Six Sigma guidelines and employed the most rigorous and available tools which may help minimizing such a tension[4]. However, we believe that the IRI paradigms need to be introduced as the basis for the whole campus community to embrace the new changes. The IRI is not just about statistics, tools or SAS codes. It is more profound and bigger than that technical stuff. It is about the campus cultural change. It is about the attitude change. It is about embracing the new world; the future and it is not just about a college's survival. Rather, it affects the country's competitiveness in the global market.

The first three tables above show that both White and Hispanic male students from Texas are more likely to drop out their program. The next question that one may ask is what kind of programs that most of the drop-out students are having trouble with? The data scientist can run other codes to answer this question by modifying the above codes and add "program" variable in the `Table` statement to come out with the following results:

Table 4 - Drop-out Students Profile by Program and Age

Prg/Age	16	18	19	20	21	23	Total
CA	1	0	2	0	0	0	3
CB	0	0	0	0	0	1	1
CC	0	1	0	0	1	1	3
DB	0	0	1	1	0	0	2
DC	0	0	0	1	0	1	2
S4	0	1	1	1	0	0	3
Total	1	2	4	3	1	3	14

[4] Applying these concepts will not guarantee automatic improvements of the retention rate. We have seen unfavorable, little if none improvements on student retention or graduation rate.

Table 5 - Drop-out Student Profile by Program and Gender

Prg/Gender	F	M	Total
CA	0	3	3
CB	1	0	1
CC	0	3	3
DB	0	2	2
DC	0	2	2
S4	2	1	3
Total	3	11	14

Table 6 - Drop-out Student Profile by Program and Ethnicity

Prg/Eth	A	B	H	W	Total
CA	1	2	0	0	3
CB	0	0	0	1	1
CC	1	0	1	1	3
DB	1	0	0	1	2
DC	0	1	1	0	2
S4	0	0	2	1	3
Total	3	3	4	4	14

The first letter in the program name (Prg) refers to either certificate (C) or diploma (D), respectively. The second letter indicates different concentrations or majors such as nursing, radiology or others. S4 refers to 4 year program leading to an undergraduate degree. It is pretty obvious that most the drop-out students are coming from the CC program. This information can then be used by the administrators to communicate with the program director or chairperson to further analyze what has hindered the students to finish their program. In the next step of the assessment process, it is wise to apply the qualitative analyses to find other information which can be used to remove the potential roadblocks so that students may finish their studies as planned. Therefore, applying the ***qualitative research*** approaches is a relevant step to go deeper in the analyses. The most common qualitative research that has been applied by many colleges is focus group. However, class observations, student interview and documents (syllabus) reviews are all appropriate to be done at this level. These ***meticulous*** efforts are new, required and will become common standard operating procedures (SOP) for colleges to cope with the new realities facing the industry. These procedures improve and increase the resilient of those colleges to deal with a more turbulence industry. Applying the IRI paradigms will increase the probability of colleges' future success as previously discussed and shown above.

Concluding Remarks:

The old IR approach may no longer be suitable and therefore unfit to cope with the recent and more complex education issues. Needless to say over a hundred years this "old" approach does not recognize the potential problems by only focusing on the reporting aspects. As results, US colleges keep recycling the same stuff and treat the problem as "BAU". The old ways seem not to encourage colleges to operate with the most efficient way for they can pass all the "waste" or any inefficiency to the borrowers. Sadly, they, the borrowers have to absorb the burdens for years by taking loans. On August 14, 2013, there is a report which stated about 7 million student loan borrowers are at default and the total loans have surpassed a $1 trillion mark (John Sandman, 2013) which then trigger the regulator to implement the CAR rule. The time has arrived to change the old way with new IRI (Institutional Research Intelligence) paradigms as suggested by the Association of American Education Analytics (http://www.aaea.us/). Colleges need to have data scientist with education analytics expertise and training who can help them to get out of the water. AAEA's current research results show that almost all US colleges operating expenses are way higher than what they have made from tuition revenue. About 519 institutions are under water as measured by their debt-to-equity ratio (DER) and the amount of liabilities over the net assets is $137 billion. Therefore, college survival will be affected greatly with any regulators' policy changes, except for institutions that have accumulated huge endowment fund. Even with the enormous amount of endowment money, it needs to be managed professionally. Perhaps, this is one of the reasons why Harvard University recently hired a new risk investment officer to oversee their $30.7 billion endowment as reported by Reuter on June 19, 2013 (Svea Herbst-Bayliss', 2013). The Bipartisan Student Loans Certainty Act of 2013 signed by the regulator on August 9, 2013 along with the CAR regulation which has just been announced on August 22nd, 2013 are the two real examples of the many dynamic changes that are happening in the education industry and make higher learning industry is more volatile. One might expect many more policy changes are coming their way and these changes could happen anytime in the future without prior notice.

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John Sandman., $1 Trillion in Student Loans and 7 Million Borrowers in Default, MainStreet, New York, Published on August 14, 2013.

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Svea Herbst-Bayliss'., Harvard hires Xia from Morgan Stanley as chief risk officer, Reuters, Published on June 19, 2013.

Appendix 1 – List of Drop-out Students

Students Information			Programs or Majors	Credentials		
StudentID	**HS_State**	**HS_Name**	**Program_Code**	**High School GPA**	**COMP ACT SCORE**	**Dropped-Out-Flag**
1	TX	A	S4	2	21.00	.
2	TX	C	CA	2.3	27.00	.
3	TX	D	CC	3.1	29.00	.
4	TX	A	CB	2.4	25.00	.
5	TX	D	CA	2.67	24.00	.
6	TX	C	DB	3	23.00	.
7	AR	B	DC	2.9	30.00	.
8	OK	E	S4	3.4	32.00	.
9	TX	A	S4	4	29.00	.
10	MS	F	CB	2	29.00	.
11	AR	B	CC	2.9	18.00	.
12	TX	A	CA	3.5	21.00	.
13	TX	A	DB	2.15	22.00	.

Students Information			Programs or Majors	Credentials		
StudentID	HS_State	HS_Name	Program_Code	High School GPA	COMP ACT SCORE	Dropped-Out-Flag
14	TX	D	DC	3.7	27.00	.
15	TX	C	S4	3.4	29.00	.
16	AR	B	DC	2.05	21.00	.
17	OK	E	CB	2.9	22.00	.
18	TX	C	CA	3.4	19.00	.
19	AR	B	CA	3.8	29.00	.
20	OK	E	CC	2	28.00	.
21	TX	A	S4	3.3	25.00	.
22	MS	F	S4	3.4	27.00	.
23	AR	B	CB	3.8	19.00	.
24	TX	A	CB	3	20.00	.
25	TX	A	CA	2.8	16.00	.
26	TX	D	DC	2.9	18.00	.
27	TX	A	S4	2	29.00	.
28	TX	D	DA	3.8	28.00	.
29	TX	C	CB	3.9	24.00	.
30	AR	B	CC	2.1	30.00	.
31	OK	E	DC	4	31.00	.
32	TX	A	DC	2.08	21.00	.
33	MS	F	S4	3.9	27.00	.
34	TX	C	CA	2.19	29.00	.
35	AR	B	CB	2.6	25.00	.
36	OK	E	CA	3.5	24.00	.
37	TX	A	DB	3.9	23.00	.
38	MS	F	DA	3.5	30.00	.
39	AR	B	S4	3.2	32.00	.
40	TX	A	CC	3	29.00	.
41	TX	A	DA	2.8	29.00	.
42	TX	D	CA	2.9	18.00	.
43	TX	A	CC	2	21.00	.
44	TX	D	DB	3.4	22.00	.
45	TX	D	S4	3.7	27.00	.

Students Information			Programs or Majors	Credentials		
StudentID	HS_State	HS_Name	Program_Code	High School GPA	COMP ACT SCORE	Dropped-Out-Flag
46	TX	A	DC	3.9	29.00	.
47	TX	D	CB	2	19.00	.
48	TX	C	CA	2.1	26.00	.
49	AR	B	CA	3.4	30.00	.
50	OK	E	DC	2.2	20.00	.
51	TX	A	DC	2.3	30.00	.
52	MS	F	DA	2.09	32.00	.
53	TX	C	S4	2	23.00	.
54	AR	B	CB	2	30.00	.
55	OK	E	DB	3.4	28.00	.
56	TX	A	DB	2.38	27.00	.
57	TX	C	S4	3.4	19.00	.
58	TX	D	CC	4	33.00	.
59	TX	A	CB	2.9	32.00	.
60	TX	D	DA	2.8	30.00	.
61	TX	C	CC	2.6	34.00	.
62	AR	B	CB	2.7	25.00	.
63	OK	E	CA	2.28	26.00	.
64	TX	A	S4	3.4	22.00	.
65	AR	B	CB	2.9	28.00	.
66	OK	E	CB	2.29	30.00	.
67	TX	A	DA	3.7	23.00	.
68	MS	F	S4	3.6	24.00	.
69	TX	C	S4	3.9	21.00	.
70	AR	B	S4	2.49	26.00	.
71	OK	E	S4	3.8	22.00	.
72	TX	A	CC	3.9	20.00	.
73	TX	C	CC	3.5	30.00	.
74	MS	F	DA	3.4	21.00	.
75	AR	B	DB	2.29	29.00	.
76	TX	A	CA	3.4	28.00	.
77	TX	A	S4	2.6	27.00	.

Students Information			Programs or Majors	Credentials		
StudentID	HS_State	HS_Name	Program_Code	High School GPA	COMP ACT SCORE	Dropped-Out-Flag
78	TX	D	CB	2.8	29.00	.
79	TX	A	DC	2.9	25.00	.
80	TX	D	S4	3	24.00	.
81	TX	C	DA	2.2	23.00	.
82	AR	B	CB	3.4	30.00	.
83	OK	E	CA	3	32.00	.
84	TX	A	CA	3.2	29.00	.
85	MS	F	S4	2.9	29.00	.
86	TX	C	DB	2.8	18.00	.
87	TX	A	CC	2.7	21.00	.
88	MS	F	CC	3.9	22.00	.
89	TX	C	CA	4	27.00	.
90	AR	B	DA	3.5	29.00	.
91	OK	E	S4	2	21.00	.
92	TX	A	CA	2.8	30.00	.
93	TX	C	S4	2.6	32.00	.
94	MS	F	CB	3.5	29.00	.
95	AR	B	S4	2	29.00	.
96	TX	A	DB	2.6	18.00	.
97	TX	A	CC	2.8	21.00	.
98	TX	D	S4	3.4	22.00	.
99	TX	A	CA	3.9	27.00	.
100	TX	D	S4	2.8	29.00	.
101	TX	C	CA	2.28	19.00	.
102	MS	F	CA	3.4	26.00	.
103	AR	B	S4	4	30.00	.
104	TX	A	CC	2.9	20.00	.
105	TX	A	CA	2.8	30.00	.
106	TX	D	DB	2.6	32.00	.
107	TX	A	DB	2.7	23.00	.
108	TX	D	S4	2.18	30.00	.
109	TX	C	DA	3.4	19.00	.

Students Information			Programs or Majors	Credentials		
StudentID	HS_State	HS_Name	Program_Code	High School GPA	COMP ACT SCORE	Dropped-Out-Flag
110	AR	B	CA	2.9	20.00	.
111	OK	E	CC	2.19	16.00	.
112	TX	A	CC	3.7	18.00	.
113	MS	F	DB	3.6	29.00	.
114	TX	C	S4	3.9	28.00	.
115	TX	A	CA	2.59	24.00	.
116	MS	F	DC	3.8	30.00	.
117	TX	C	DB	3.9	31.00	.
118	AR	B	DA	3.5	21.00	.
119	AR	B	S4	3.4	27.00	.
120	OK	E	CC	3.19	29.00	.
121	TX	A	CA	3.4	32.00	.
122	MS	F	DB	2.6	29.00	.
123	TX	C	CB	2.8	29.00	.
124	AR	B	S4	2	18.00	.
125	OK	E	DA	2.3	21.00	.
126	TX	A	DB	3.1	22.00	.
127	MS	F	CA	2.4	27.00	.
128	AR	B	S4	2.67	29.00	.
129	TX	A	DA	3	19.00	.
130	TX	A	CB	2.39	26.00	.
131	TX	D	CC	3.4	30.00	.
132	TX	A	S4	4	20.00	.
133	TX	D	DB	2	30.00	.
134	TX	D	CA	2.9	32.00	.
135	TX	A	CB	3.5	23.00	.
136	TX	D	S4	2.45	30.00	.
137	TX	C	DA	3.7	28.00	.
138	AR	B	DB	3.4	27.00	.
139	OK	E	S4	2.25	19.00	.
140	TX	A	DA	2.9	33.00	.
141	MS	F	CA	3.4	32.00	.

Students Information			Programs or Majors	Credentials		
StudentID	HS_State	HS_Name	Program_Code	High School GPA	COMP ACT SCORE	Dropped-Out-Flag
142	AR	B	CA	3.8	30.00	.
143	OK	E	S4	2	34.00	.
144	TX	A	CA	3.3	25.00	.
145	MS	F	S4	3.8	26.00	.
146	TX	C	DB	2	22.00	.
147	AR	B	CA	3.3	28.00	.
148	OK	E	DB	3.4	30.00	.
149	TX	A	S4	3.8	23.00	.
150	MS	F	DB	3	24.00	.
151	AR	B	CC	2.8	21.00	.
152	TX	A	DA	2.9	26.00	.
153	TX	A	CA	2	22.00	.
154	TX	D	S4	3.8	20.00	.
155	TX	A	DA	3.9	30.00	.
156	TX	D	DC	2.1	21.00	.
157	TX	D	S4	4	29.00	.
158	TX	A	CC	2.28	28.00	.
159	TX	D	DA	3.9	27.00	.
160	TX	C	S4	2.56	29.00	.
161	AR	B	CA	2.6	28.00	.
162	OK	E	CC	3.5	23.00	.
163	TX	A	S4	3.9	20.00	.
164	MS	F	CA	3.5	30.00	.
165	AR	B	S4	3.2	29.00	.
166	OK	E	CC	3	25.00	.
167	TX	A	DA	2.8	23.00	.
168	MS	F	DA	2.9	21.00	.
169	TX	C	CC	2	29.00	.
170	AR	B	S4	3.4	26.00	.
171	OK	E	DA	3.7	27.00	.
172	TX	A	DB	3.9	21.00	.
173	MS	F	CC	2	19.00	.

Students Information			Programs or Majors	Credentials		
StudentID	HS_State	HS_Name	Program_Code	High School GPA	COMP ACT SCORE	Dropped-Out-Flag
174	AR	B	DC	2.1	18.00	.
175	TX	A	DA	3.4	22.00	.
176	TX	A	CB	2.2	28.00	.
177	TX	D	S4	2.3	18.00	.
178	TX	A	CC	2.79	27.00	.
179	TX	D	CB	2	23.00	.
180	TX	D	S4	2	29.00	.
181	TX	A	DA	3.4	20.00	.
182	TX	D	DB	2.38	22.00	.
183	TX	C	S4	3.4	27.00	.
184	AR	B	S4	4	26.00	.
185	OK	E	CC	2.9	22.00	.
186	TX	A	S4	2.8	32.00	.
187	MS	F	S4	2.6	33.00	.
188	AR	B	CA	2.7	31.00	.
189	OK	E	CC	3.18	23.00	.
190	TX	A	DA	3.4	28.00	.
191	MS	F	CC	2.9	27.00	.
192	TX	C	S4	2.8	26.00	.
193	AR	B	CA	2.6	29.00	.
194	OK	E	DB	2.7	20.00	.
195	TX	A	DA	3.9	19.00	.
196	MS	F	CA	3.4	18.00	.
197	AR	B	DC	2.9	29.00	.
198	TX	A	DA	2.79	20.00	.
199	TX	A	S4	3.7	28.00	.
200	TX	D	DB	3.6	27.00	.