Predicting Post-College Earnings

CS593

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Team:

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Problem Statement

- Choosing the right college can be one of the most important decisions one makes
- The median annual salary of college graduates was nearly $25k higher than that of those with only a high school diploma
    - Bureau of Labor Statistics
- We wanted to find a better way to help prospective students choose a college based on potential earnings
- Similarly, we wanted to see what are the most important features in student earnings post graduation, and whether they are due to the school itself or outside factors

Project Framework

1. Clean Data
2. Process Data
3. Multiple Linear Regression
    a. Check Assumptions
    b. Run Regression Model
4. Synthesize Results

Data Source and Description

- College Scorecard Data from the US Department of Education
    - “The College Scorecard is designed to increase transparency, putting the power in the hands of the public — from those choosing colleges to those improving college quality — to see how well different schools are serving their students.”
- Yearly report on colleges based on many facets including:
    - Academics, admissions, aid, completion, cost, earnings, repayment, and student demographics
- Contains 1899 columns, 7703 rows

Data Cleaning and Preprocessing

- Made the decision to use the 2014-2015 dataset for the most recent year that still had relatively complete information.
- Then removed all columns that contained no information.
- Decided the response variable should be ‘MD_EARN_WNE_P10’, which represents: “Median earnings of students working and not enrolled 10 years after entry”
- Removed all other fields related to earnings, as well as any fields that were strings or unique identifiers
- This left 1427 out of 1899 columns

Data Cleaning and Preprocessing

- We found that there were many entries in the data labeled either “Null” or “PrivacySuppressed”
- We treated these both as ‘null’ values, and removed all columns with over 20% ‘null’ data
- For the remaining numerical columns, we replaced null values with the median value
- For the remaining categorical columns, we used a one-hot encoding to create dummy variables
- Similarly, we removed any rows for which the response variable was null.

Final Dataset Description

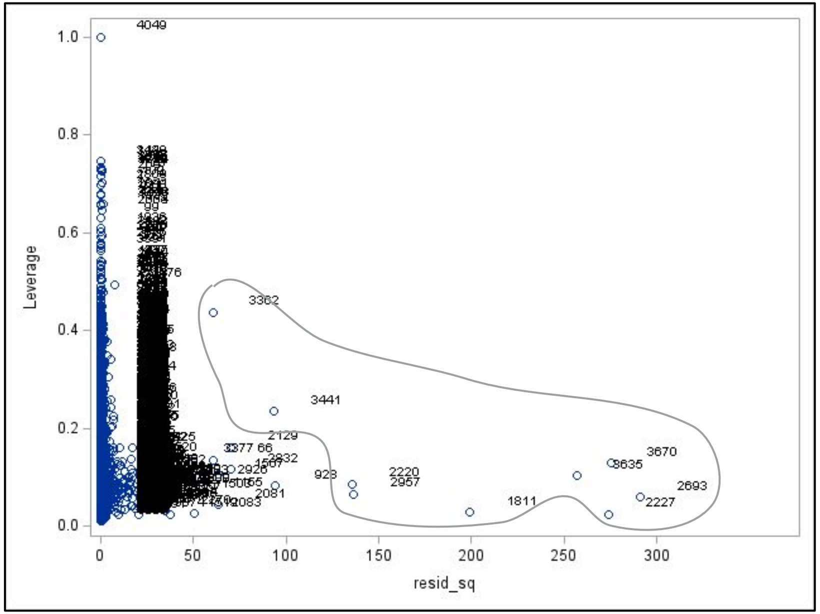
Final dataset used consisted of 152 numerical variables, 199 categorical variables transformed into 622 dummy variables over 6062 rows/schools

Check for the **5 Underlying Assumptions**

- Linear relationship ✅
- Residual normality for the dependent variable ✅
- No or little multicollinearity ✅
- No autocorrelation ✅
- Homoscedasticity ✅
- (Remove Outliers) ✅

1. Removing **Outliers** (6062 rows -> 5819 rows)

- **Leverage - Residual Plot:**



- **Cook's Distance (cookd <= 4/n):**
  - n = 6062
  - 4/6062 = 0.0006598...

```
*Print data with large Cook's Distance;
PROC PRINT DATA=stdres;
    WHERE cookd > (4/6062);
    VAR cookd MD_EARN_WNE_P10 &num_Var &cat_Var;
RUN;
```

The SAS System

Obs	cookd	MD_EARN_WNE_P10	NUMBRANCH	TUITFTE	INEXPFTE	COMP_ORIG_YR2_RT	WDRAW_ORIG_YR2_RT	LO_INC_COMP_ORIG_YR2_R
56	0.001400	0.7324320158	-0.327780117	-0.564875106	0.3937100912	-1.015179094	1.1354368817	-1.11684461
67	0.017229	5.4948984826	-0.327780117	8.1429693817	5.4078431619	-0.390243777	-0.115920781	-0.32604835
105	0.000784	-0.218749303	-0.327780117	-1.108659581	-0.358702725	-0.966425485	1.5631045099	-1.05666850
110	0.002013	0.345399617	-0.327780117	-0.978448327	-0.554803131	-1.266876055	1.2283493765	-1.36995980
112	0.003012	-1.537283408	-0.327780117	-0.864016236	-0.114731743	-0.390243777	1.0538328434	-0.32604835
174	0.002453	0.2863607765	-0.327780117	1.9867085682	0.5673958041	-1.266368316	0.9568830464	-1.36996043
193	0.003338	0.9292281508	-0.327780117	-0.256717311	-0.471902557	2.2203563238	-0.115920781	2.502021009
200	0.001600	3.3891798382	-0.327780117	0.852597714	9.6294647696	-0.390243777	-0.115920781	-0.32604835
223	0.001606	7.1807853724	-0.327780117	1.1290645831	12.341980553	-0.390243777	-0.115920781	-0.32604835
229	0.000853	3.1923837032	-0.327780117	-0.325403084	0.9155556864	-1.078775375	-1.457208301	-0.32604835
242	0.001088	-0.408985567	-0.327780117	-1.2412576	-0.30407395	-0.390243777	0.8572541066	-0.32604835

2. Check for **Linear Relationship**

- Checked for **correlation** between **dependent variables** and **each independent variable**
- **Remove** variables with **insignificant correlation scores** (5819, **774 cols**) -> (5819, **407 cols**)

```
PROC CORR DATA=DATA2z;
    VAR &num_Var &cat_Var;
    WITH MD_EARN_WNE_P10;
RUN;
```

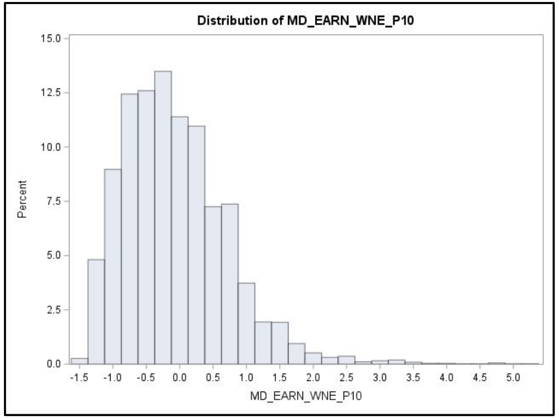
Pearson Correlation Coefficients, N = 5819 Prob > |r| under H0: Rho=0						
	NUMBRANCH	TUITFTE	INEXPFTE	COMP_ORIG_YR2_RT	WDRAW_ORIG_YR2_RT	LO_INC_COMP_ORIG_YR2_RT
MD_EARN_WNE_P10	0.05841 <.0001	0.40544 <.0001	0.47809 <.0001	-0.37902 <.0001	-0.24355 <.0001	-0.27573 <.0001

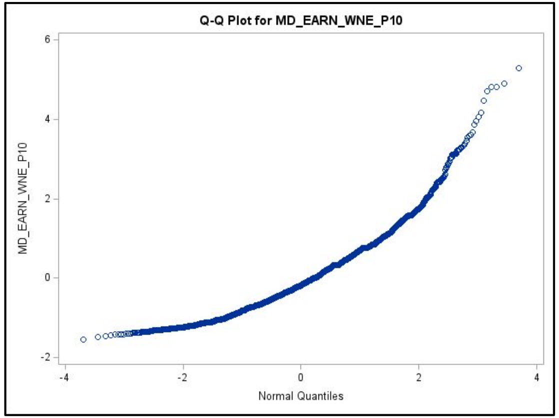
3. **Normally distributed residual** (Dependent)

Moments			
N	5819	Sum Weights	5819
Mean	-0.0635276	Sum Observations	-369.66698
Std Deviation	0.79405819	Variance	0.6305284
Skewness	1.12645076	Kurtosis	2.7953164
Uncorrected SS	3691.8983	Corrected SS	3668.41425
Coeff Variation	-1249.9425	Std Error Mean	0.01040946

Tests for Normality				
Test	Statistic		p Value	
Kolmogorov-Smirnov	D	0.14084	Pr > D	<0.0100
Cramer-von Mises	W-Sq	56.19521	Pr > W-Sq	<0.0050
Anderson-Darling	A-Sq	324.2841	Pr > A-Sq	<0.0050

<= 0.05





4. Check for **Homoscedasticity**

- **Homoscedasticity** == **Equal variance of the residuals** for each independent variables
- 400+ residual plots; Results check out

```
PROC REG DATA=DATA2z PLOTS(MAXPOINTS=NONE);
    MODEL MD_EARN_WNE_P10 = &xlist;
    PLOT R.*P.;
RUN;
QUIT;
```

Residual   Predicted Value

5. Check for **Multicollinearity**

- VIF (Variance Inflation)
- *If VIF is **greater than 5**, there is a multicollinearity problem in the model.*
- **SAS REG module** assigns 0s to the rest of the collinear variables

Parameter Estimates						
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	B	-0.14210	0.04121	-3.45	0.0006	0
NUMBRANCH	1	0.05860	0.01914	3.06	0.0022	28.91377
TUITFTE	1	0.03536	0.00796	4.44	<.0001	3.75538
INEXPFTE	1	0.14270	0.00814	17.53	<.0001	2.16803
COMP_ORIG_YR2_RT	1	-0.01624	0.01359	-1.20	0.2321	14.09202
WDRAW_ORIG_YR2_RT	1	-0.05692	0.01566	-3.64	0.0003	18.60225
LO_INC_COMP_ORIG_YR2_RT	1	0.01203	0.01343	0.90	0.3706	13.80706
LO_INC_WDRAW_ORIG_YR2_RT	1	-0.02776	0.01472	-1.89	0.0594	16.63776
DEP_COMP_ORIG_YR2_RT	1	0.01576	0.01449	1.09	0.2768	16.26952
IND_COMP_ORIG_YR2_RT	1	0.00637	0.01438	0.44	0.6577	15.94369
FIRSTGEN_COMP_ORIG_YR2_RT	1	-0.06246	0.02290	-2.73	0.0064	40.44200
FIRSTGEN_WDRAW_ORIG_YR2_RT	1	-0.02990	0.01871	-1.60	0.1102	26.79794
NOT1STGEN_COMP_ORIG_YR2_RT	1	0.05747	0.02335	2.46	0.0139	41.96746
NOT1STGEN_WDRAW_ORIG_YR2_RT	1	0.09461	0.01816	5.21	<.0001	25.18103
WDRAW_ORIG_YR3_RT	1	0.02215	0.01470	1.51	0.1321	16.43080
WDRAW_4YR_TRANS_YR3_RT	1	0.00781	0.00660	1.18	0.2367	3.25783
LO_INC_COMP_ORIG_YR3_RT	1	-0.00258	0.01335	-0.19	0.8465	13.55447
LO_INC_WDRAW_ORIG_YR3_RT	1	0.02566	0.01151	2.23	0.0259	10.19278
DEP_COMP_ORIG_YR3_RT	1	-0.03597	0.01476	-2.44	0.0148	16.79939
IND_COMP_ORIG_YR3_RT	1	0.01371	0.01485	0.92	0.3558	16.93306
FEMALE_COMP_ORIG_YR3_RT	1	-0.02622	0.01593	-1.65	0.0998	19.26861
MALE_COMP_ORIG_YR3_RT	1	0.00761	0.01477	0.52	0.6064	16.48092
FIRSTGEN_COMP_ORIG_YR3_RT	1	0.01018	0.01353	0.75	0.4519	13.94995
FIRSTGEN_WDRAW_ORIG_YR3_RT	1	-0.04729	0.01462	-3.24	0.0012	16.46642
NOT1STGEN_WDRAW_ORIG_YR3_RT	1	-0.01089	0.01540	-0.71	0.4797	18.25810
COMP_ORIG_YR4_RT	1	0.06425	0.01369	4.69	<.0001	14.01476
WDRAW_ORIG_YR4_RT	1	0.02453	0.01392	1.76	0.0781	14.68921
WDRAW_2YR_TRANS_YR4_RT	1	-0.01067	0.00490	-2.18	0.0293	1.86663

6. Check for **Autocorrelation**

- Check **DW score** for Autocorrelation
- *A DW value **between 1.5 and 2.5** confirms the absence of first-order autocorrelation.*

Durbin-Watson D	1.914
Number of Observations	5819
1st Order Autocorrelation	0.043

Linear Regression - Results

```
*Simple Linear Regression;
PROC REG DATA=DATA2z;
    MODEL MD_EARN_WNE_P10 = &xlist
               / SELECTION=NONE;
    OUTPUT OUT=REG_DATA2zOUT_01
    H=lev COOKD=Cookd DFFITS=dffit;
RUN;
QUIT;
```

The REG Procedure
Model: MODEL1
Dependent Variable: MD_EARN_WNE_P10

Number of Observations Read	5819
Number of Observations Used	5819

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	360	3251.05656	9.03071	118.10	<.0001
Error	5458	417.35769	0.07647		
Corrected Total	5818	3668.41425			

Root MSE	0.27653	R-Square	0.8862
Dependent Mean	-0.06353	Adj R-Sq	0.8787
Coeff Var	-435.28645		

Linear Regression - **Forward**, **Stepwise** Results

```
*SELECTION = Forward;
PROC REG DATA=DATA2z;
    MODEL MD_EARN_WNE_P10 = &xlist
                / SELECTION=FORWARD;
    OUTPUT OUT=REG_DATA2zOUT_1
    H=lev COOKD=Cookd DFFITS=dffit;
RUN;
QUIT;
```

Forward Selection: Step 253

Variable CIP51BACHL_1_0 Entered: R-Square = 0.8859 and C(p) = 165.0370

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	253	3249.67733	12.84457	170.70	<.0001
Error	5565	418.73693	0.07524		
Corrected Total	5818	3668.41425			

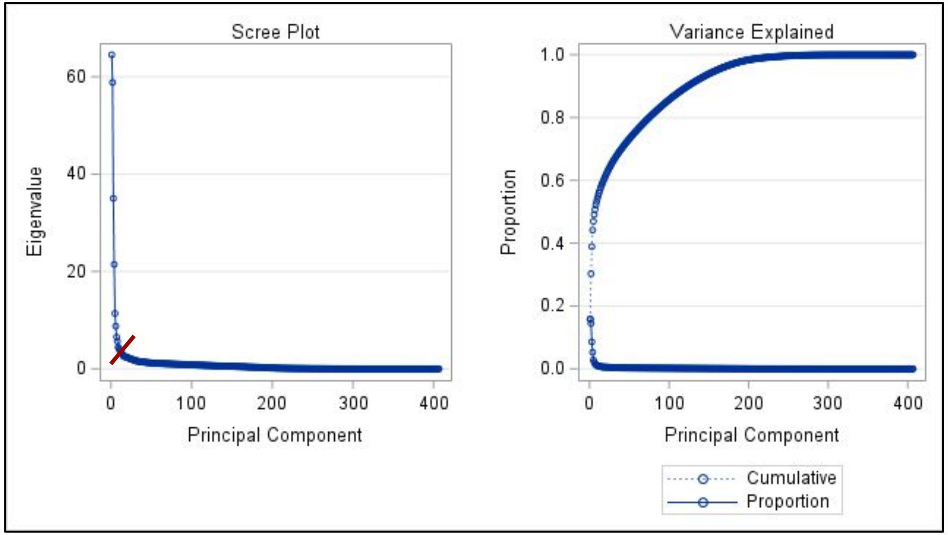
```
*SELECTION = Stepwise;
PROC REG DATA=DATA2z;
    MODEL MD_EARN_WNE_P10 = &xlist
                / SELECTION=STEPWISE;
    OUTPUT OUT=REG_DATA2zOUT_2
    H=lev COOKD=Cookd DFFITS=dffit;
RUN;
QUIT;
```

Stepwise Selection: Step 196

Variable CIP27BACHL_2_0 Entered: R-Square = 0.8835 and C(p) = 101.9477

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	164	3240.89043	19.76153	261.35	<.0001
Error	5654	427.52382	0.07561		
Corrected Total	5818	3668.41425			

PCA - Results



Eigenvalues of the Correlation Matrix				
	Eigenvalue	Difference	Proportion	Cumulative
1	64.5325619	5.6695623	0.1586	0.1586
2	58.8629997	23.8328295	0.1446	0.3032
3	35.0301701	13.5682005	0.0861	0.3893
4	21.4619696	10.0670216	0.0527	0.4420
5	11.3949480	2.6275978	0.0280	0.4700
6	8.7673502	2.2070610	0.0215	0.4915
7	6.5602892	0.8946829	0.0161	0.5076
8	5.6656063	1.1984786	0.0139	0.5216
9	4.4671277	0.3174751	0.0110	0.5325
10	4.1496526	0.2740117	0.0102	0.5427
11	3.8756410	0.4479179	0.0095	0.5523
12	3.4277231	0.1677368	0.0084	0.5607
13	3.2599863	0.1439199	0.0080	0.5687
14	3.1160665	0.3998530	0.0077	0.5763
15	2.7162134	0.0936871	0.0067	0.5830
16	2.6225263	0.0382850	0.0064	0.5895
17	2.5842414	0.1218059	0.0063	0.5958
18	2.4624355	0.0809576	0.0061	0.6019
19	2.3814779	0.0292096	0.0059	0.6077
20	2.3522683	0.0331648	0.0058	0.6135
21	2.3191035	0.0953053	0.0057	0.6192
22	2.2237982	0.1033722	0.0055	0.6247
23	2.1204260	0.0335985	0.0052	0.6299
24	2.0868275	0.0879171	0.0051	0.6350
25	1.9989104	0.0374834	0.0049	0.6399
26	1.9614270	0.0482918	0.0048	0.6447

Linear Regression with PCA - Results

The REG Procedure
Model: MODEL1
Dependent Variable: MD_EARN_WNE_P10

Number of Observations Read	5819
Number of Observations Used	5819

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	2394.88867	133.04937	605.94	<.0001
Error	5800	1273.52558	0.21957		
Corrected Total	5818	3668.41425			

Root MSE	0.46859	R-Square	0.6528
Dependent Mean	-0.06353	Adj R-Sq	0.6518
Coeff Var	-737.61127		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.06353	0.00614	-10.34	<.0001
Prin1	1	-0.01154	0.00076474	-15.09	<.0001
Prin2	1	0.06449	0.00080072	80.54	<.0001
Prin3	1	-0.02255	0.00104	-21.73	<.0001
Prin4	1	0.02079	0.00133	15.68	<.0001
Prin5	1	0.03604	0.00182	19.80	<.0001
Prin6	1	0.05035	0.00207	24.27	<.0001
Prin7	1	0.06112	0.00240	25.48	<.0001
Prin8	1	0.03389	0.00258	13.13	<.0001
Prin9	1	-0.03475	0.00291	-11.96	<.0001
Prin10	1	-0.02845	0.00302	-9.43	<.0001
Prin11	1	-0.02838	0.00312	-9.10	<.0001
Prin12	1	0.02055	0.00332	6.19	<.0001
Prin13	1	0.03504	0.00340	10.30	<.0001
Prin14	1	0.02278	0.00348	6.55	<.0001
Prin15	1	0.01279	0.00373	3.43	0.0006
Prin16	1	-0.05414	0.00379	-14.27	<.0001
Prin17	1	-0.07624	0.00382	-19.95	<.0001
Prin18	1	-0.09244	0.00391	-23.61	<.0001

Important Variables (Linear Regression Stepwise Selection)

- Entirely Graduate-Degree Granting
- Instructional expenditures per full-time equivalent student
- Share of female students
- Average family income of dependent students in real 2015 dollars.
- Number of students in the cumulative loan debt cohort
- Control of institution - Public
- Share of students who received a Pell Grant while in school
- Predominant degree awarded - Certificate
- Predominant degree awarded - Associate
- Percentage of students who are financially independent
- Level of institution - Less than 2 year
- Average family income of independent students in real 2015 dollars.
- Bachelor's degree in Education.
- Bachelor's degree in Visual And Performing Arts.
- The median debt for no-Pell students
- % Aided students with family incomes between $75,001-$110,000 in nominal dollars

RED = Negative Impact

Results Interpretation

- Of the most impactful variables in this dataset, many have less to do with the school, and more to do with demographics of the school
    - Average Family Income, Percent of students who are financially independent, Gender
- Many also were related to the degree type offered
    - Schools that were entirely graduate-degree offering was by far the most impactful variable
    - Schools that primarily awarded Associate’s degrees or certificates were negatively impactful
    - Schools offering degrees in Education and Visual and Performing Arts also had a negative impact in earnings. (Lower on the list was that Engineering degrees increased later earnings)
- That said, the second most impactful feature was ‘Instructional expenditures per full-time equivalent student’
    - This shows that there is a tangible benefit to students in schools spend money toward instruction, though correlation doesn’t necessarily imply causation
    - Interesting that public schools also exhibited higher earnings

Conclusions

Instructional spending on students was indeed a big factor, though whether that's a cause or an effect is left for debate

Type of Degree, both the level and the field, is an important factor regarding future earnings

Outside factors also have a considerable effect on future earnings

Overall, we indeed were able to create a significant model to predict future earnings based on the College Scorecard Dataset

Next Steps

If we were to take this problem further some things we would look at include:

- Restricting our variables to factors that a college can control
- Looking at the actual cause and effect relationships between some of the variables
- Take other years worth of data to see what the impact is over time and over a larger dataset
- See what was not significant or not included

Thanks for Listening

Questions?

Data Source: https://collegescorecard.ed.gov/data/

Honor pledge: I pledge on my honor that I have not given or received any unauthorized assistance on this assignment/examination. I further pledge that I have not copied any material from a book, article, the Internet or any other source except where I have expressly cited the source.

Appendix:

Full list of fields in final model:

Variable	Programmer-Friendly Name
PREDDEG_4	degrees_awarded.predominant
INEXPFTE	instructional_expenditure_per_fte
FEMALE	demographics.female_share
DEP_INC_AVG	avg_dependent_income.2014dollars
CUML_DEBT_N	cumulative_debt.number
FIRSTGEN_DEBT_N	median_debt.number.first_generation_students
CONTROL_1	ownership
PELL_EVER	students_with_pell_grant
SCH_DEG_1_0	degrees_awarded.predominant_recoded
NOTFIRSTGEN_DEBT_N	median_debt.number.non_first_generation_students
SCH_DEG_2_0	degrees_awarded.predominant_recoded
DEP_STAT_PCT_IND	share_independent_students
ICLEVEL_3	institutional_characteristics.level
IND_INC_AVG	avg_independent_income.2014dollars
CIP13BACHL_0_0	program.bachelors.education
MALE_YR4_N	4_yr_completion.male_students
CIP50BACHL_1_0	program.bachelors.visual_performing
NOPELL_DEBT_MDN	median_debt.no_pell_grant
IND_YR2_N	2_yr_completion.independent_students
INC_PCT_H1	share_highincome.75001_110000
FAMINC	demographics.avg_family_income
CIP14BACHL_1_0	program.bachelors.engineering
MARRIED	demographics.married
CONTROL_2	ownership

Appendix:

Full list of fields in final model:

NOPELL_DEBT_N	median_debt.number.no_pell_grant
TUITFTE	tuition_revenue_per_fte
PAR_ED_PCT_MS	share_firstgeneration_parents.middleschool
CIP09CERT4_1_0	program.certificate_lt_4_yr.communication
CIP12CERT4_1_0	program.certificate_lt_4_yr.personal_culinar y
APPL_SCH_PCT_GE3	fafsa_sent.3_college_allyrs
IND_DEBT_N	median_debt.number.independent_students
DEBT_MDN	loan_principal
DEBT_MDN_SUPP	median_debt_suppressed.overall
NUMBRANCH	#N/A
ST_FIPS_50	#N/A
DEP_INC_N	family_income.dependent_students
CIP50CERT4_1_0	program.certificate_lt_4_yr.visual_performin g
NOPELL_YR4_N	4_yr_completion.no_pell_grant
REGION_0	region_id
FIRSTGEN_YR3_N	3_yr_completion.first_generation_students
CIP51CERT4_1_0	program.certificate_lt_4_yr.health
FEMALE_DEBT_N	median_debt.number.female_students
FIRSTGEN_YR2_N	2_yr_completion.first_generation_students
NOT1STGEN_WDRAW_ORIG_YR2_RT	title_iv.not_first_gen.withdrawn_by.2yrs
IND_DEBT_MDN	median_debt.independent_students
CUML_DEBT_P75	cumulative_debt.75th_percentile
COMP_ORIG_YR4_RT	title_iv.completed_by.4yrs

Appendix:

Full list of fields in final model:

CIP52BACHL_0_0	program.bachelors.business_marketing
LO_INC_YR3_N	3_yr_completion.low_income
CUML_DEBT_P25	cumulative_debt.25th_percentile
CIP11BACHL_0_0	program.bachelors.computer
DEP_YR2_N	2_yr_completion.dependent_students
FEMALE_DEBT_MDN	median_debt.female_students
ST_FIPS_25	#N/A
CIP26BACHL_1_0	program.bachelors.biological
CIP52CERT1_0_0	program.certificate_lt_1_yr.business_marketing
MAIN_1	#N/A
WDRAW_ORIG_YR2_RT	title_iv.withdrawn_by.2yrs
AGE_ENTRY	demographics.age_entry
CIP51BACHL_0_0	program.bachelors.health
PREDDEG_3	#N/A
CIP52ASSOC_1_0	program.assoc.business_marketing
CIP12CERT1_1_0	program.certificate_lt_1_yr.personal_culinary
CIP12BACHL_1_0	program.bachelors.personal_culinary
FIRSTGEN_WDRAW_ORIG_YR2_RT	title_iv.first_gen.withdrawn_by.2yrs
CIP40ASSOC_1_0	program.assoc.physical_science
ST_FIPS_9	#N/A
CIP12CERT2_1_0	program.certificate_lt_2_yr.personal_culinary
REGION_2	region_id
HIGHDEG_3	#N/A
PELL_DEBT_MDN	median_debt.pell_grant
MALE_DEBT_N	median_debt.number.male_students

Appendix:

Full list of fields in final model:

CIP31BACHL_1_0	program.bachelors.parks_recreation_fitness
CIP40BACHL_1_0	program.bachelors.physical_science
IND_INC_PCT_LO	share_independent_lowincome.0_30000
PAR_ED_PCT_HS	share_firstgeneration_parents.highschool
CIP24ASSOC_1_0	program.assoc.humanities
INC_PCT_M2	share_middleincome.48001_75000
NOLOAN_YR4_N	4_yr_completion.no_loan_students
PELL_YR3_N	3_yr_completion.pell_grant
CIP45BACHL_2_0	program.bachelors.social_science
CIP44BACHL_1_0	program.bachelors.public_administration_social_service
REGION_7	region_id
MD_INC_YR2_N	2_yr_completion.middle_income
CIP15CERT2_1_0	program.certificate_lt_2_yr.engineering_technology
ST_FIPS_21	#N/A
CIP29BACHL_2_0	program.bachelors.military
DEP_YR4_N	4_yr_completion.dependent_students
CIP39CERT4_2_0	program.certificate_lt_4_yr.theology_religious_vocation
CIP22CERT1_2_0	program.certificate_lt_1_yr.legal
CIP39BACHL_0_0	program.bachelors.theology_religious_vocation
HI_INC_DEBT_MDN	median_debt.income.greater_than_75000
FEMALE_YR2_N	2_yr_completion.female_students
CIP31CERT1_1_0	program.certificate_lt_1_yr.parks_recreation_fitness
CIP11BACHL_1_0	program.bachelors.computer
MD_INC_YR3_N	3_yr_completion.middle_income

Appendix:

Full list of fields in final model:

CIP50BACHL_2_0	program.bachelors.visual_performing
CIP13ASSOC_0_0	program.assoc.education
INC_PCT_LO	share_lowincome.0_30000
ST_FIPS_18	#N/A
CIP04BACHL_1_0	program.bachelors.architecture
CIP03ASSOC_1_0	program.assoc.resources
CIP47BACHL_2_0	program.bachelors.mechanic_repair_technology
CIP51CERT1_1_0	program.certificate_lt_1_yr.health
LO_INC_WDRAW_ORIG_YR3_RT	title_iv.low_inc.withdrawn_by.3yrs
CIP24BACHL_0_0	program.bachelors.humanities
ST_FIPS_46	#N/A
CIP11CERT4_2_0	program.certificate_lt_4_yr.computer
NOTFIRSTGEN_DEBT_MDN	median_debt.non_first_generation_students
CIP43CERT1_0_0	program.certificate_lt_1_yr.security_law_enforcement
WDRAW_DEBT_MDN	median_debt.noncompleters
ST_FIPS_36	#N/A
ST_FIPS_30	#N/A
CIP44CERT4_1_0	program.certificate_lt_4_yr.public_administration_social_service
CIP14CERT4_1_0	program.certificate_lt_4_yr.engineering
CIP27BACHL_2_0	program.bachelors.mathematics
REGION_1	#N/A
ST_FIPS_55	#N/A
ST_FIPS_33	#N/A
MALE_DEBT_MDN	median_debt.male_students
ST_FIPS_2	#N/A
CIP46BACHL_2_0	program.bachelors.construction