

Homework 2 - Grant Jackson

September 6, 2024

```
[1]: import os
os.chdir('C:\\Users\\gmoor\\Documents\\Economic Analytics 1\\Data')
```

```
[2]: import numpy as np
import pandas as pd
import math
```

```
[3]: raw0 = pd.read_csv('College.csv')
```

```
[4]: raw0.head()
```

```
[4]:
```

		Unnamed: 0	Private	Apps	Accept	Enroll	Top10perc	\
0	Abilene Christian University		Yes	1660	1232	721	23	
1	Adelphi University		Yes	2186	1924	512	16	
2	Adrian College		Yes	1428	1097	336	22	
3	Agnes Scott College		Yes	417	349	137	60	
4	Alaska Pacific University		Yes	193	146	55	16	

	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Personal	\
0	52	2885	537	7440	3300	450	2200	
1	29	2683	1227	12280	6450	750	1500	
2	50	1036	99	11250	3750	400	1165	
3	89	510	63	12960	5450	450	875	
4	44	249	869	7560	4120	800	1500	

	PhD	Terminal	S.F.Ratio	perc.alumni	Expend	Grad.Rate
0	70	78	18.1	12	7041	60
1	29	30	12.2	16	10527	56
2	53	66	12.9	30	8735	54
3	92	97	7.7	37	19016	59
4	76	72	11.9	2	10922	15

```
[5]: # Convert "private" variable to a dummy using a built-in function
raw0['Private']=pd.get_dummies(raw0['Private'],drop_first=True,dtype=float)
```

```
[6]: raw0.Private
```

```
[6]: 0      1.0
      1      1.0
      2      1.0
      3      1.0
      4      1.0
      ...
      772    0.0
      773    1.0
      774    1.0
      775    1.0
      776    1.0
      Name: Private, Length: 777, dtype: float64
```

```
[7]: # Change the column name perc.alumni
raw0.rename(columns = {'perc.alumni': 'palumni'}, inplace = True)
```

```
[8]: raw0.head()
```

```
[8]:
```

		Unnamed: 0	Private	Apps	Accept	Enroll	Top10perc	\
0	Abilene Christian University		1.0	1660	1232	721	23	
1	Adelphi University		1.0	2186	1924	512	16	
2	Adrian College		1.0	1428	1097	336	22	
3	Agnes Scott College		1.0	417	349	137	60	
4	Alaska Pacific University		1.0	193	146	55	16	

	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Personal	\
0	52	2885	537	7440	3300	450	2200	
1	29	2683	1227	12280	6450	750	1500	
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3	89	510	63	12960	5450	450	875	
4	44	249	869	7560	4120	800	1500	

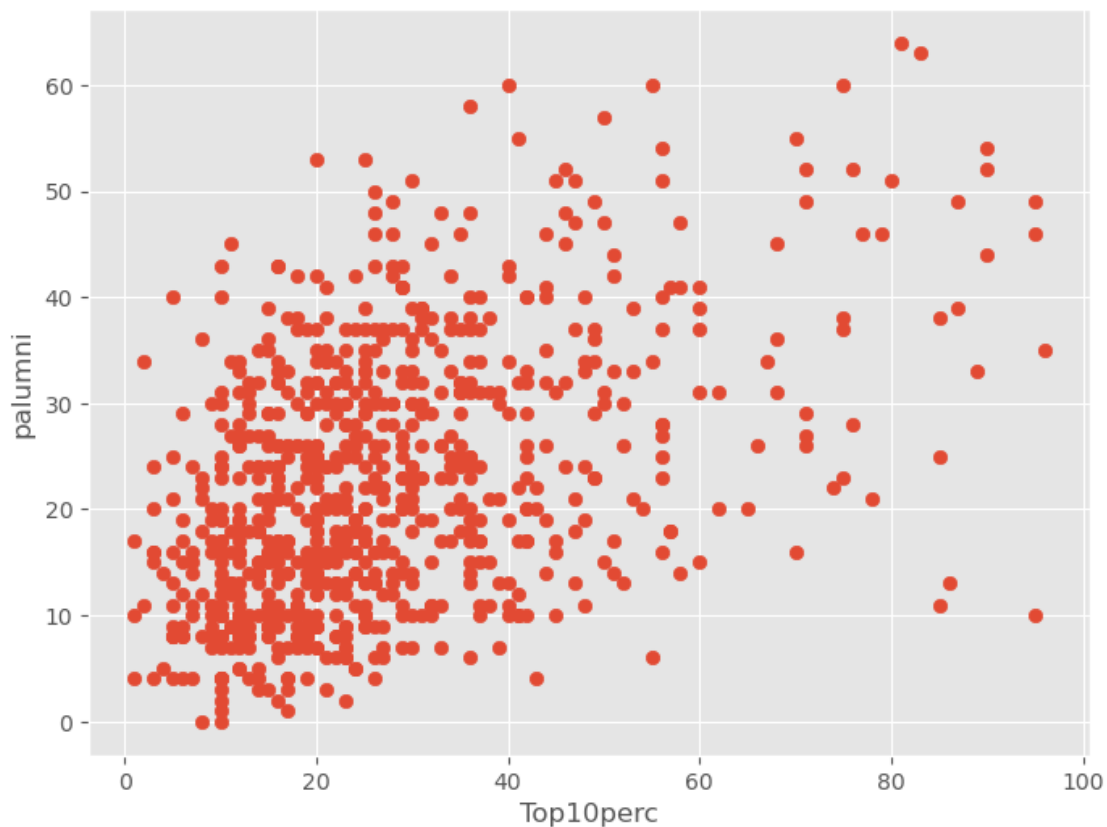
	PhD	Terminal	S.F.Ratio	palumni	Expend	Grad.Rate
0	70	78	18.1	12	7041	60
1	29	30	12.2	16	10527	56
2	53	66	12.9	30	8735	54
3	92	97	7.7	37	19016	59
4	76	72	11.9	2	10922	15

0.0.1 Plotting Library: matplotlib.pyplot

- matplotlib.pyplot is a collection of functions for creating static, animated, and interactive visualizations in Python.
 1. Introduction: <https://matplotlib.org/tutorials/index.html>
 2. Useful examples and codes: <https://matplotlib.org/gallery/index.html>
 3. Style reference: https://matplotlib.org/3.2.1/gallery/style_sheets/style_sheets_reference.html

```
[9]: # Simple scatter plot
import matplotlib.pyplot as plt

plt.style.use('ggplot')
plt.figure(figsize=(8, 6), dpi=100)
plt.scatter('Top10perc', 'palumni', data=raw0)
plt.xlabel('Top10perc')
plt.ylabel('palumni')
#plt.savefig('scatter.png') # Will save picture of scatter plot into your data_
    ↪ folder
plt.show()
```



0.0.2 Running OLS using “statsmodels”

- statsmodels.formula.api provides an interface for specifying models using formula strings and DataFrames. (API reference: <https://www.statsmodels.org/stable/api.html>)
- Useful examples and codes: <https://www.statsmodels.org/stable/examples/index.html>

```
[10]: # Import statsmodels.formula.api
import statsmodels.formula.api as smf
```

```
# Fit a regression model
OLSres = smf.ols('palumni ~ Top10perc + Outstate', data=raw0).fit()
```

```
[11]: # A summary of the result
print(OLSres.summary())
```

```

OLS Regression Results
=====
Dep. Variable:          palumni    R-squared:                0.348
Model:                  OLS        Adj. R-squared:           0.346
Method:                 Least Squares    F-statistic:            206.7
Date:                  Wed, 04 Sep 2024    Prob (F-statistic):      1.21e-72
Time:                  18:37:44    Log-Likelihood:          -2891.5
No. Observations:      777        AIC:                    5789.
Df Residuals:          774        BIC:                    5803.
Df Model:               2
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	4.2776	1.001	4.273	0.000	2.312	6.243
Top10perc	0.1408	0.025	5.711	0.000	0.092	0.189
Outstate	0.0014	0.000	12.923	0.000	0.001	0.002

```

=====
Omnibus:                23.166    Durbin-Watson:           1.950
Prob(Omnibus):           0.000    Jarque-Bera (JB):        24.444
Skew:                    0.418    Prob(JB):                 4.92e-06
Kurtosis:                3.236    Cond. No.                 3.12e+04
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 3.12e+04. This might indicate that there are strong multicollinearity or other numerical problems.

```
[12]: # interaction and higer order terms
OLSres = smf.ols('palumni ~ np.power(Top10perc,2) + Top10perc:Outstate',
data=raw0).fit()
print(OLSres.summary())
```

```

OLS Regression Results
=====
Dep. Variable:          palumni    R-squared:                0.326
Model:                  OLS        Adj. R-squared:           0.324
Method:                 Least Squares    F-statistic:            187.3
Date:                  Wed, 04 Sep 2024    Prob (F-statistic):      4.64e-67

```

```

Time:                  18:37:44    Log-Likelihood:          -2904.4
No. Observations:      777        AIC:                      5815.
Df Residuals:          774        BIC:                      5829.
Df Model:               2
Covariance Type:       nonrobust

```

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```

	coef	std err	t	P> t	[0.025
Intercept	14.8920	0.547	27.203	0.000	13.817
np.power(Top10perc, 2)	-0.0039	0.001	-6.582	0.000	-0.005
Top10perc:Outstate	3.687e-05	2.74e-06	13.476	0.000	3.15e-05

```

=====
Omnibus:                22.532    Durbin-Watson:           1.960
Prob(Omnibus):           0.000    Jarque-Bera (JB):        23.726
Skew:                    0.421    Prob(JB):                7.05e-06
Kurtosis:                3.157    Cond. No.:               6.92e+05
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 6.92e+05. This might indicate that there are strong multicollinearity or other numerical problems.

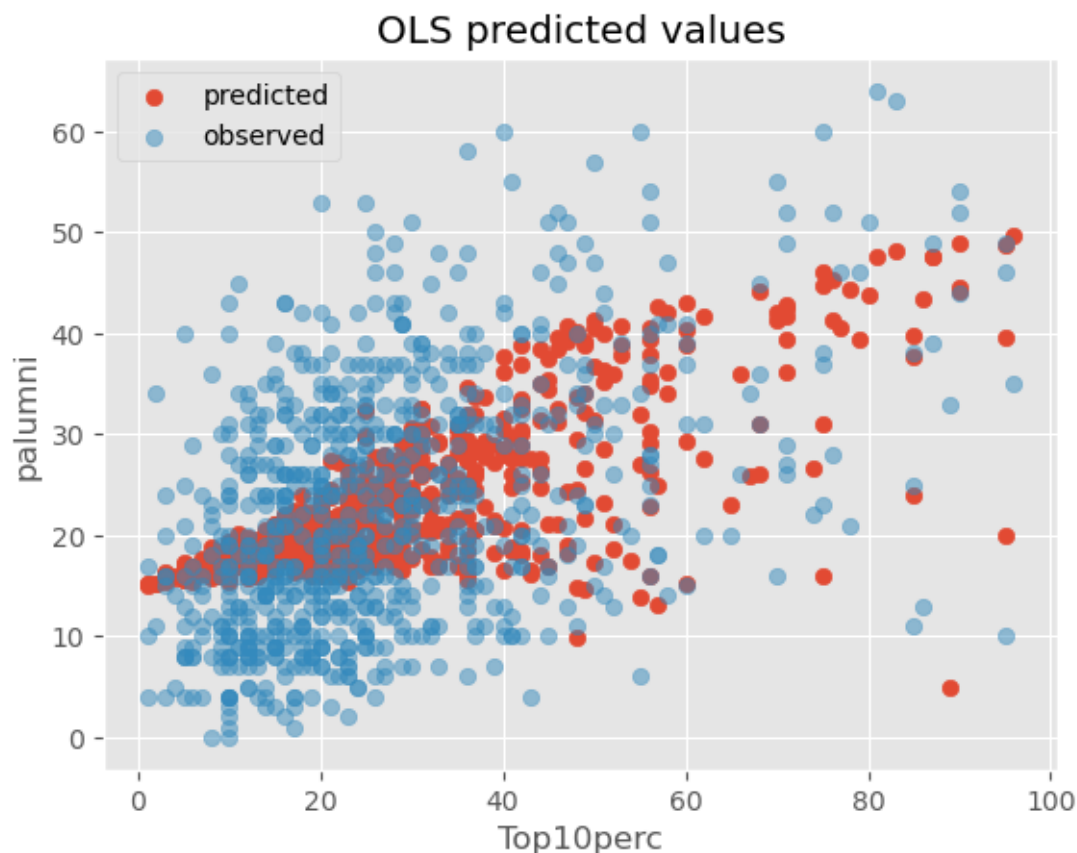
```

[13]: # Scatterplot fitted(predicted) values (palumni ~ Top10perc)

plt.scatter(raw0['Top10perc'], OLSres.predict(), alpha=1, label='predicted') #_
    ↪fitted / alpha changes the transparency of the plotted points
plt.scatter(raw0['Top10perc'], raw0['palumni'], alpha=0.5, label='observed') #_
    ↪original

plt.legend()
plt.title('OLS predicted values')
plt.xlabel('Top10perc')
plt.ylabel('palumni')
plt.show()

```



```
[14]: # Access individual estimate:
# https://www.statsmodels.org/stable/generated/statsmodels.regression.
# linear_model.OLSResults.html#statsmodels.regression.linear_model.OLSResults

OLSres.params # parameter estimates
```

```
[14]: Intercept                14.892000
np.power(Top10perc, 2)        -0.003948
Top10perc:Outstate            0.000037
dtype: float64
```

```
[15]: ### <font color='green'> Making a table for multiple regressions using
# statsmodels.iolib.summary2"
```

```
[16]: OLS1 = smf.ols('palumni ~ Top10perc', data=raw0).fit()
OLS2 = smf.ols('palumni ~ Top10perc + Private + Outstate', data=raw0).fit()
OLS3 = smf.ols('palumni ~ Top10perc + Private + Outstate + Personal + Expend',
# data=raw0).fit()
```

```
[17]: from statsmodels.iolib.summary2 import summary_col

info_dict={'BIC' : lambda x: x.bic,
          'No. observations' : lambda x: f"{int(x.nobs)}"}

# "dictionary" is another way to store data, which use "keys" to index elements
# ↪ (instead of numbers): key-value pair
# e.g., A = {"BIC":40} and then type A["BIC"] to get 40
# e.g., A = [40,50,60] and then type A[0] to get 40

# lambda is a function to define a function, which define a parameter then a
# ↪ function: https://www.w3schools.com/python/python\_lambda.asp

results_table = summary_col(results=[OLS1,OLS2,OLS3],
                           float_format='%0.2f',
                           stars = True,
                           model_names=['Model 1',
                                         'Model 2',
                                         'Model 3'],
                           # info_dict=info_dict,
                           regressor_order=['Intercept',
                                             'Top10perc',
                                             'Private',
                                             'Outstate',
                                             'Personal',
                                             'Expend'])

results_table.add_title('OLS Regressions')

print(results_table)
```

	OLS Regressions		
	Model 1	Model 2	Model 3
Intercept	13.93*** (0.73)	3.74*** (0.99)	7.94*** (1.43)
Top10perc	0.32*** (0.02)	0.17*** (0.02)	0.18*** (0.03)
Private		5.50*** (0.97)	4.86*** (0.98)
Outstate		0.00*** (0.00)	0.00*** (0.00)
Personal			-0.00*** (0.00)
Expend			-0.00 (0.00)
R-squared	0.21	0.37	0.39

R-squared Adj. 0.21 0.37 0.38

=====

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01

0.0.3 HW2: Pick five combinations of the regressors to explain the percent of alumni. The regressors may include interactions of two variables or squared/cubed variables.

1. Run five regressions with each combination
2. Produce a table summarizing the results of your five regressions as above

0.0.4 One of you will present your regression results in the coming python session. Please check/interpret your regression results carefully

```
[18]: # Number 1

import statsmodels.formula.api as smf
import pandas as pd

# Define the 5 different regression models
# Basic Model, Top10perc and Outstate are regressors
OLS1 = smf.ols('palumni ~ Top10perc + Outstate', data=raw0).fit()

# Same as above, but adding Private to the regressors
OLS2 = smf.ols('palumni ~ Top10perc + Outstate + Private', data=raw0).fit()

# Same as above, but adding Apps to the regressors
OLS3 = smf.ols('palumni ~ Top10perc + Outstate + Private + Apps', data=raw0).
    ↪fit()

# Introducing an interaction term between Top10perc and Outstate
OLS4 = smf.ols('palumni ~ Top10perc + Outstate + Top10perc:Outstate',
    ↪data=raw0).fit()

# Adding Expend to the regressors from Model 2
OLS5 = smf.ols('palumni ~ Top10perc + Outstate + Private + Expend', data=raw0).
    ↪fit()
```

```
[19]: # Number 2

from statsmodels.iolib.summary2 import summary_col

info_dict={'BIC' : lambda x: x.bic,
           'No. observations' : lambda x: f"{int(x.nobs)}"}

# Building table with each regression result
results_table = summary_col(results=[OLS1, OLS2, OLS3, OLS4, OLS5],
```



```

float_format='%0.2f',
stars = True,
model_names=['Model 1', 'Model 2', 'Model 3',
↳'Model 4', 'Model 5'],
regressor_order=['Intercept', 'Top10perc',
↳'Outstate', 'Private',
'Personal', 'Expend', 'Top10perc:
↳Outstate'])

results_table.add_title('OLS Regressions for Percent of Alumni')

print(results_table)

```

```

OLS Regressions for Percent of Alumni
=====

```

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	4.28*** (1.00)	3.74*** (0.99)	5.23*** (1.02)	3.99** (1.90)	3.76*** (0.99)
Top10perc	0.14*** (0.02)	0.17*** (0.02)	0.21*** (0.03)	0.15** (0.06)	0.18*** (0.03)
Outstate	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Private		5.50*** (0.97)	2.77** (1.12)		5.45*** (0.98)
Expend					-0.00 (0.00)
Top10perc:Outstate				-0.00 (0.00)	
Apps			-0.00*** (0.00)		
R-squared	0.35	0.37	0.39	0.35	0.37
R-squared Adj.	0.35	0.37	0.39	0.35	0.37

```

=====

```

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01

[]: