

Preparing data

In Breast Cancer Wisconsin (Prognostic) Data Set Each record represents follow-up data for one breast cancer case. These are consecutive patients seen by Dr. Wolberg since 1984, and include only those cases exhibiting invasive breast cancer and no evidence of distant metastases at the time of diagnosis.

These are attributes that sample-code-number is just an ID and we don't count it a feature, and the class attribute is our output for regression.

#	Attribute	Domain
--	-----	-----
1.	Sample code number	id number
2.	Clump Thickness	1 - 10
3.	Uniformity of Cell Size	1 - 10
4.	Uniformity of Cell Shape	1 - 10
5.	Marginal Adhesion	1 - 10
6.	Single Epithelial Cell Size	1 - 10
7.	Bare Nuclei	1 - 10
8.	Bland Chromatin	1 - 10
9.	Normal Nucleoli	1 - 10
10.	Mitoses	1 - 10
11.	Class:	(2 for benign, 4 for malignant)

First of all we need to remove the Data that have missing values (16 row).

Analysis

Linear regression

We have 9 Features, we calculated the regression for this features, and save the result of them in Results Data

In this Model we have coefficient from 0.23, all p-values have the same values, so they have same importance. There is some thing that surprise us and it was the small coefficients for all features, but we understood that because of our X's that are in {1,2,3,4,5,6,7,8,,9,10} and our y that are in {2,4} the coefficients always are near 0.2

- R-squared: R-squared is a statistical measure of how close the data are to the fitted regression line
- p-value : When we perform a hypothesis test in statistics, a p-value helps us determine the significance of your results.
- Adjusted R-squared : The adjusted R-squared is a modified version of R-squared that has been adjusted for the number of predictors in the model. The adjusted R-squared increases only if the new term improves the model more than would be expected by chance. It decreases when a predictor improves the model by less than expected by chance

- F-statistics : The F value is the ratio of the mean regression sum of squares divided by the mean error sum of squares. Its value will range from zero to an arbitrarily large number. The value of Prob(F) is the probability that the null hypothesis for the full model is true (that all of the regression coefficients are zero).

1. bareNuclei

OLS Regression Results					
=====					
=					
Dep. Variable:	class	R-squared:			
0.677					
Model:	OLS	Adj. R-squared:			
0.676					
Method:	Least Squares	F-statistic:			
1426.					
Date:	Sun, 14 Oct 2018	Prob (F-statistic):			
3.40e-169					
Time:	18:21:25	Log-Likelihood:			
-551.15					
No. Observations:	683	AIC:			
1106.					
Df Residuals:	681	BIC:			
1115.					
Df Model:	1				
Covariance Type:	nonrobust				
=====					
=					
	coef	std err	t	P> t	[0.025
0.975]					

-					
const	1.9359	0.029	66.754	0.000	1.879
1.993					
bareNuclei	0.2155	0.006	37.766	0.000	0.204
0.227					
=====					
=					
Omnibus:	218.770	Durbin-Watson:			
1.791					
Prob(Omnibus):	0.000	Jarque-Bera (JB):			
796.545					
Skew:	1.479	Prob(JB):			
1.08e-173					
Kurtosis:	7.386	Cond. No.			
7.23					
=====					
=					

p-value is 0.000 so this feature is significant R-squared is 0.677 do the data almost have a good fit with regression line Prob(f-statistics) is so small so the null hypothesis for features in this model is not true

2. clump thickness

OLS Regression Results					
=====					
=					
Dep. Variable:	class	R-squared:			
0.511					
Model:	OLS	Adj. R-squared:			
0.510					
Method:	Least Squares	F-statistic:			
711.4					
Date:	Sun, 14 Oct 2018	Prob (F-statistic):			
7.29e-108					
Time:	18:21:25	Log-Likelihood:			
-692.64					
No. Observations:	683	AIC:			
1389.					
Df Residuals:	681	BIC:			
1398.					
Df Model:	1				
Covariance Type:	nonrobust				
=====					
=====					
	coef	std err	t	P> t	[0.025
0.975]					

const	1.6253	0.048	34.065	0.000	1.532
1.719					
clumpThickness	0.2419	0.009	26.673	0.000	0.224
0.260					
=====					
=					
Omnibus:	46.918	Durbin-Watson:			
1.742					
Prob(Omnibus):	0.000	Jarque-Bera (JB):			
54.786					
Skew:	0.676	Prob(JB):			
1.27e-12					

Kurtosis: 3.314 Cond. No. 10.1

p-value is 0.000 so this feature is significant R-squared is 0.511 do the data almost have a good fit with regression line Prob(f-statistics) is so small so the null hypothesis for features in this model is not true

3. uniformity of cell size

OLS Regression Results					
=====					
=					

```

Dep. Variable:          class    R-squared:
0.674
Model:                  OLS      Adj. R-squared:
0.673
Method:                 Least Squares    F-statistic:
1406.
Date:                   Sun, 14 Oct 2018    Prob (F-statistic):
8.92e-168
Time:                   18:21:25    Log-Likelihood:
-554.42
No. Observations:      683    AIC:
1113.
Df Residuals:          681    BIC:
1122.
Df Model:              1
Covariance Type:       nonrobust

```

```

=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
const              1.8944      0.030     63.242      0.000      1.836
1.953
uniformityOfCellSize  0.2556      0.007     37.498      0.000      0.242
0.269
=====
=
Omnibus:           141.261    Durbin-Watson:
1.769
Prob(Omnibus):     0.000    Jarque-Bera (JB):
268.178
Skew:              1.191    Prob(JB):
5.83e-59
Kurtosis:          4.937    Cond. No.
6.48
=====
=

```

p-value is 0.000 so this feature is significant R-squared is 0.674 do the data almost have a good fit with regression line Prob(f-statistics) is so small so the null hypothesis for features in this model is not true

4. uniformity of cell shape

```

              OLS Regression Results
=====
=
Dep. Variable:          class    R-squared:
0.676
Model:                  OLS      Adj. R-squared:
0.675
Method:                 Least Squares    F-statistic:
1418.

```

```

Date: Sun, 14 Oct 2018 Prob (F-statistic):
1.37e-168
Time: 18:21:25 Log-Likelihood:
-552.54
No. Observations: 683 AIC:
1109.
Df Residuals: 681 BIC:
1118.
Df Model: 1
Covariance Type: nonrobust
=====
=====
                                coef    std err          t      P>|t|      [0.025
0.975]
-----
const                1.8558      0.031     60.654      0.000      1.796
1.916
uniformityOfCellShape  0.2625      0.007     37.652      0.000      0.249
0.276
=====
=
Omnibus:                111.909   Durbin-Watson:
1.849
Prob(Omnibus):          0.000   Jarque-Bera (JB):
189.327
Skew:                   1.013   Prob(JB):
7.73e-42
Kurtosis:               4.595   Cond. No.
6.63
=====
=

```

p-value is 0.000 so this feature is significant R-squared is 0.675 do the data almost have a good fit with regression line Prob(f-statistics) is so small so the null hypothesis for features in this model is not true

5. marginal adhesion

```

                                OLS Regression Results
=====
=
Dep. Variable:                class   R-squared:
0.499
Model:                        OLS     Adj. R-squared:
0.498
Method:                       Least Squares   F-statistic:
677.9
Date: Sun, 14 Oct 2018   Prob (F-statistic):
2.98e-104
Time: 18:21:25   Log-Likelihood:
-700.97
No. Observations:          683   AIC:
1406.

```

```

Df Residuals:          681    BIC:
1415.
Df Model:              1
Covariance Type:      nonrobust
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
const          2.0337      0.036     55.888      0.000      1.962
2.105
marginalAdhesion  0.2354      0.009     26.036      0.000      0.218
0.253
=====
=
Omnibus:          126.961    Durbin-Watson:
1.629
Prob(Omnibus):      0.000    Jarque-Bera (JB):
199.005
Skew:              1.240    Prob(JB):
6.12e-44
Kurtosis:          3.915    Cond. No.
5.84
=====
=

```

p-value is 0.000 so this feature is significant R-squared is 0.498 do the data fitted with regression line not -bad Prob(f-statistics) is so small so the null hypothesis for features in this model is not true

6. single epithelial cell size

```

              OLS Regression Results
=====
=
Dep. Variable:      class    R-squared:
0.477
Model:              OLS     Adj. R-squared:
0.477
Method:              Least Squares    F-statistic:
622.2
Date:                Sun, 14 Oct 2018    Prob (F-statistic):
4.73e-98
Time:                18:21:25    Log-Likelihood:
-715.27
No. Observations:    683    AIC:
1435.
Df Residuals:        681    BIC:
1444.
Df Model:              1
Covariance Type:      nonrobust
=====
=====

```

		coef	std err	t	P> t
[0.025	0.975]				

const		1.7403	0.047	37.287	0.000
1.649	1.832				
singleEpithelialCellSize		0.2967	0.012	24.943	0.000
0.273	0.320				
=====					
=					
Omnibus:		68.911	Durbin-Watson:		
1.769					
Prob(Omnibus):		0.000	Jarque-Bera (JB):		
87.713					
Skew:		0.831	Prob(JB):		
8.98e-20					
Kurtosis:		3.564	Cond. No.		
7.24					
=====					
=					

p-value is 0.000 so this feature is significant R-squared is 0.477 do the data fitted with regression line not -bad Prob(f-statistics) is so small so the null hypothesis for features in this model is not true

7. bland chromatin

OLS Regression Results					
=====					
=					
Dep. Variable:	class	R-squared:			
0.575					
Model:	OLS	Adj. R-squared:			
0.574					
Method:	Least Squares	F-statistic:			
921.0					
Date:	Sun, 14 Oct 2018	Prob (F-statistic):			
1.27e-128					
Time:	18:21:25	Log-Likelihood:			
-644.76					
No. Observations:	683	AIC:			
1294.					
Df Residuals:	681	BIC:			
1303.					
Df Model:	1				
Covariance Type:	nonrobust				
=====					
=====					
	coef	std err	t	P> t	[0.025
0.975]					

const	1.6820	0.041	40.878	0.000	1.601
1.763					

```

blandChromatin      0.2955      0.010      30.348      0.000      0.276
0.315
=====
=
Omnibus:              84.860   Durbin-Watson:
1.821
Prob(Omnibus):        0.000   Jarque-Bera (JB):
118.645
Skew:                 0.899   Prob(JB):
1.72e-26
Kurtosis:             3.968   Cond. No.
7.57
=====
=

```

p-value is 0.000 so this feature is significant R-squared is 0.575 do the data almost have a good fit with regression line Prob(f-statistics) is so small so the null hypothesis for features in this model is not true

8. normal nucleoli

```

                                OLS Regression Results
=====
Dep. Variable:                  class   R-squared:
0.516
Model:                          OLS    Adj. R-squared:
0.516
Method:                         Least Squares   F-statistic:
727.5
Date:                           Sun, 14 Oct 2018   Prob (F-statistic):
1.47e-109
Time:                           18:21:25   Log-Likelihood:
-688.73
No. Observations:                683   AIC:
1381.
Df Residuals:                    681   BIC:
1391.
Df Model:                        1
Covariance Type:                 nonrobust
=====
=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
const                2.0549      0.035      58.886      0.000      1.986
2.123
normalNucleoli       0.2247      0.008      26.972      0.000      0.208
0.241
=====
=
Omnibus:              147.506   Durbin-Watson:
1.848

```



```

Prob(Omnibus):          0.000   Jarque-Bera (JB):
254.504
Skew:                  1.328   Prob(JB):
5.43e-56
Kurtosis:              4.374   Cond. No.
5.91
=====
=

```

p-value is 0.000 so this feature is significant R-squared is 0.677 do the data almost have a good fit with regression line Prob(f-statistics) is so small so the null hypothesis for features in this model is not true

9. mitoses

```

=====
                                OLS Regression Results
=====
Dep. Variable:                class   R-squared:
0.179
Model:                        OLS     Adj. R-squared:
0.178
Method:                        Least Squares   F-statistic:
148.8
Date:                          Sun, 14 Oct 2018   Prob (F-statistic):
4.30e-31
Time:                          18:21:25   Log-Likelihood:
-869.41
No. Observations:              683   AIC:
1743.
Df Residuals:                  681   BIC:
1752.
Df Model:                      1
Covariance Type:              nonrobust
=====
=

```

	coef	std err	t	P> t	[0.025
0.975]					

-					
const	2.3258	0.045	51.536	0.000	2.237
2.414					
mitoses	0.2333	0.019	12.198	0.000	0.196
0.271					

```


=====
=
Omnibus:                    226.302   Durbin-Watson:
1.665
Prob(Omnibus):              0.000   Jarque-Bera (JB):
110.185
Skew:                      0.839   Prob(JB):
1.18e-24
Kurtosis:                  1.972   Cond. No.
3.51
=====

```

```
=====
```

p-value is 0.000 so this feature is significant R-squared is 0.179 do the data fitted with regression line so bad Prob(f-statistics) is so small so the null hypothesis for features in this model is not true

plots

As you see our data you understand that all of our data X are 1 or 2 or 3, ...or 10 , and all y are 2 or 4 so our coefficient will be so small because y to x ratio is small. and all figures for our features are like this , because all plot is just 20 point, and it's because of our data set 

Multiple Linear Regression

As we see in Linear Regression all features were significant, but if we want to know that if the features are truly significant and the effects are not from other features, we calculate the multiple regression with these features and we face with this

All features multiple regression result

Dep. Variable:	class	R-squared:	0.843
Model:	OLS	Adj. R-squared:	0.841
Method:	Least Squares	F-statistic:	402.5
Date:	Wed, 10 Oct 2018	Prob (F-statistic):	4.46e-264
Time:	20:24:42	Log-Likelihood:	-303.90
No. Observations:	683	AIC:	627.8
Df Residuals:	673	BIC:	673.1
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025
0.975]					
const	1.5047	0.033	45.807	0.000	1.440
1.569					
clumpThickness	0.0634	0.007	8.898	0.000	0.049
0.077					
uniformityOfCellSize	0.0437	0.013	3.428	0.001	0.019
0.069					
uniformityOfCellShape	0.0313	0.012	2.508	0.012	0.007
0.056					
marginalAdhesion	0.0165	0.008	2.065	0.039	0.001
0.032					
singleEpithelialCellSize	0.0202	0.010	1.924	0.055	-0.000
0.041					
bareNuclei	0.0908	0.006	14.091	0.000	0.078
0.103					
blandChromatin	0.0384	0.010	3.802	0.000	0.019
0.058					
normalNucleoli	0.0371	0.007	4.981	0.000	0.022
0.052					

mitoses	0.0020	0.010	0.197	0.844	-0.018
0.021					

So the mitoses and singleEpithelialCellSize have p-value > 0.05 then these are insignificant features and we can remove them and again calculate the multiple linear regression with other 7 features and get these. and prob(F-statistic) is significant, this means at least one feature has relationship with response.

All significant features multiple regression result

Dep. Variable:	class	R-squared:	0.842
Model:	OLS	Adj. R-squared:	0.841
Method:	Least Squares	F-statistic:	515.4
Date:	Thu, 11 Oct 2018	Prob (F-statistic):	6.47e-266
Time:	21:22:05	Log-Likelihood:	-305.95
No. Observations:	683	AIC:	627.9
Df Residuals:	675	BIC:	664.1
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025
0.975]					
const	1.5318	0.030	51.224	0.000	1.473
1.591					
clumpThickness	0.0638	0.007	8.960	0.000	0.050
0.078					
uniformityOfCellSize	0.0504	0.012	4.096	0.000	0.026
0.075					
bareNuclei	0.0913	0.006	14.187	0.000	0.079
0.104					
blandChromatin	0.0386	0.010	3.833	0.000	0.019
0.058					
normalNucleoli	0.0393	0.007	5.359	0.000	0.025
0.054					
uniformityOfCellShape	0.0331	0.012	2.654	0.008	0.009
0.058					
marginalAdhesion	0.0177	0.008	2.237	0.026	0.002
0.033					

As we see in second multiple regression, R-squared decreases but this is natural because when number of features decrease then R-squared decreases too, so the best way is to compare Adjusted R-squared in two models that in these tho models are equal (0.841), so it tells us removing 2 feature doesnt decrease R-squared too much so they are not important features. In other hand we can compare Prob(F-statistics) too, that when removing 2 Features the prob(F-statistics) decreases so we can say that this deleting features give us better result.

Regularization

When Features or samples are too much , the over fitting problem may happen so we must

regularization the features and remove or some features that don't have significant p-values or shrink samples data, we use 3 ways to regularize our data in this assignment

For use the best α in formula we check from 0.01 to 100 in a loop to find best R-squared then choose that α

Ridge

Ridge regression Result

```
Alpha = 0.09
```

```
Alpha = 0.1
```

```
R-squared = 0.8433241288874997
```

	Feature	Coefficients	t values	Standard Errors	Probabilites
0	constants	1.5047	45.807	0.033	0.000
1	clumpThickness	0.0634	8.898	0.007	0.000
2	uniformityOfCellSize	0.0437	3.428	0.013	0.001
3	uniformityOfCellShape	0.0313	2.508	0.012	0.012
4	marginalAdhesion	0.0165	2.065	0.008	0.039
5	singleEpithelialCellSize	0.0202	1.924	0.010	0.055
6	bareNuclei	0.0908	14.091	0.006	0.000
7	blandChromatin	0.0384	3.801	0.010	0.000
8	normalNucleoli	0.0371	4.981	0.007	0.000
9	mitoses	0.0020	0.197	0.010	0.844

The Ridge method is based on the restriction of β_i , and the value of α is small, So we can conclude that compression is low. the p-value for mitoses (0.844) and singleEpithelialCellSize(0.055) are not small enough so in this model these features are not significant and can be remove We also observe that the p-value of other parameters in the ridge method and the multiple linear regression almost is the same, so we find that the parameters in the two methods are equally important.

Lasso

In Lasso method, we see that the mitosis coefficient is zero, so we find that this parameter has been omitted. By comparing the two methods of Lasso and Multiple Linear Regression, we observe that the p-value of marginalAdhesion, singleEpithelialCellSize, blandChromatin, the coefficient of mitoses in the lasso method is zero so we know in this model which means that the significance of these parameters is zero in this method, singleEpithelialCellSize p-value increase to (0.876) so in this model singleEpithelialCellSize is not significant, also the p-value in uniformityOfCellSize has been reduced, so it has been increased in the lasso method, and in other cases p-value is the same, we find out that the parameters have the same importance. Lasso regression Result

```
Alpha = 0.1
```

```
R-squared = 0.8402016223438626
```

	Feature	Coefficients	t values	Standard Errors	Probabilites
0	constants	1.6064	48.423	0.033	0.000
1	clumpThickness	0.0558	7.757	0.007	0.000
2	uniformityOfCellSize	0.0553	4.293	0.013	0.000
3	uniformityOfCellShape	0.0315	2.502	0.013	0.013
4	marginalAdhesion	0.0116	1.436	0.008	0.152
5	singleEpithelialCellSize	0.0017	0.156	0.011	0.876
6	bareNuclei	0.0952	14.640	0.007	0.000
7	blandChromatin	0.0256	2.514	0.010	0.012
8	normalNucleoli	0.0370	4.918	0.008	0.000
9	mitoses	0.0000	0.000	0.010	1.000

Elastic net

Elastic net regression Result The elastic net is a regularized regression method that linearly combines the L1 and L2 penalties of the lasso and ridge methods. like Lasso results we can see that also in this model mitoses coefficient is zero and has been removed.

Alpha = 0.1					
R-squared = 0.8425236919081593					
	Feature	Coefficients	t values	Standard Errors	Probabilites
0	constants	1.5567	47.270	0.033	0.000
1	clumpThickness	0.0594	8.312	0.007	0.000
2	uniformityOfCellSize	0.0488	3.819	0.013	0.000
3	uniformityOfCellShape	0.0320	2.559	0.013	0.011
4	marginalAdhesion	0.0145	1.811	0.008	0.071
5	singleEpithelialCellSize	0.0115	1.095	0.011	0.274
6	bareNuclei	0.0924	14.308	0.006	0.000
7	blandChromatin	0.0320	3.164	0.010	0.002
8	normalNucleoli	0.0370	4.961	0.007	0.000
9	mitoses	0.0000	0.000	0.010	1.000

Conclusion

As we see in results of above models we see that the R-squared in Lasso, Ridge and Elastic net doesnt increase , so for our data-set the least square regression and regularization method almos have same result

References

- [Simple and Multiple Linear Regression in Python](#)
- [How to Interpret the F-test of Overall Significance in Regression Analysis](#)