ML_Lab2

March 14, 2020

0.0.1 1. Find the url for the California Test Score Data Set from the following website:

https://vincentarelbundock.github.io/Rdatasets/datasets.html

Read through the "DOC" file to understand the variables in the dataset, then use the following url to import the data.

https://vincentarelbundock.github.io/Rdatasets/csv/Ecdat/Caschool.csv

The target data (i.e. the dependent variable) is named "testscr". You can use all variables in the data except for "readscr" and "mathscr" in the following analysis. (These two variables were used to generate the dependent variable).

[79]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import sys
import warnings

if not sys.warnoptions:
    warnings.simplefilter("ignore")
```

[2]:
```python
data = pd.read_csv("https://vincentarelbundock.github.io/Rdatasets/csv/Ecdat/
 ↪Caschool.csv")
```

0.0.2 1.1 Visualize the univariate distribution of the target feature and each of the three continuous explanatory variables that you think are likely to have a relationship with the target feature.

[3]:
```python
data.head()
```

[3]:
```
   Unnamed: 0  distcod   county                        district grspan  \
0           1    75119  Alameda              Sunol Glen Unified  KK-08
1           2    61499    Butte            Manzanita Elementary  KK-08
2           3    61549    Butte     Thermalito Union Elementary  KK-08
3           4    61457    Butte  Golden Feather Union Elementary  KK-08
4           5    61523    Butte        Palermo Union Elementary  KK-08

   enrltot   teachers    calwpct    mealpct  computer     testscr   compstu  \
0      195  10.900000   0.510200   2.040800        67  690.799988  0.343590
```

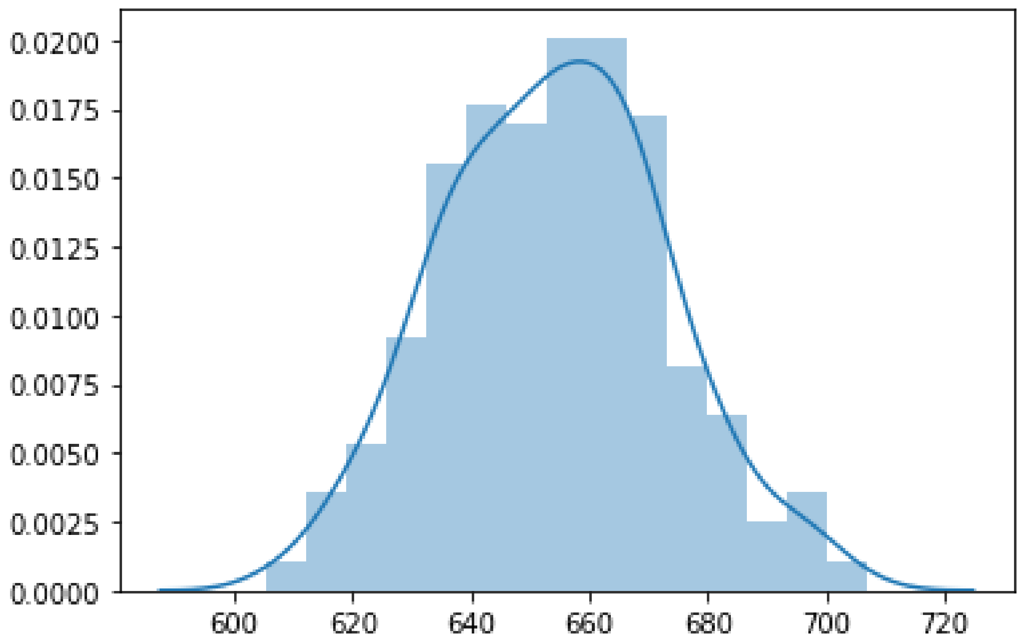
```
1      240  11.150000  15.416700  47.916698       101  661.200012  0.420833
2     1550  82.900002  55.032299  76.322601       169  643.599976  0.109032
3      243  14.000000  36.475399  77.049202        85  647.700012  0.349794
4     1335  71.500000  33.108601  78.427002       171  640.849976  0.128090

       expnstu        str     avginc      elpct     readscr     mathscr
0  6384.911133  17.889910  22.690001   0.000000  691.599976  690.000000
1  5099.380859  21.524664   9.824000   4.583333  660.500000  661.900024
2  5501.954590  18.697226   8.978000  30.000002  636.299988  650.900024
3  7101.831055  17.357143   8.978000   0.000000  651.900024  643.500000
4  5235.987793  18.671329   9.080333  13.857677  641.799988  639.900024
```

[4]:
```python
ca_schools = data.drop(['readscr','mathscr','distcod'], axis=1)
ca_schools.head()
```

[4]:
```
   Unnamed: 0   county                        district grspan  enrltot  \
0           1  Alameda              Sunol Glen Unified  KK-08      195
1           2    Butte            Manzanita Elementary  KK-08      240
2           3    Butte     Thermalito Union Elementary  KK-08     1550
3           4    Butte  Golden Feather Union Elementary  KK-08      243
4           5    Butte        Palermo Union Elementary  KK-08     1335

    teachers     calwpct    mealpct  computer     testscr    compstu  \
0  10.900000   0.510200   2.040800        67  690.799988  0.343590
1  11.150000  15.416700  47.916698       101  661.200012  0.420833
2  82.900002  55.032299  76.322601       169  643.599976  0.109032
3  14.000000  36.475399  77.049202        85  647.700012  0.349794
4  71.500000  33.108601  78.427002       171  640.849976  0.128090

       expnstu        str     avginc      elpct
0  6384.911133  17.889910  22.690001   0.000000
1  5099.380859  21.524664   9.824000   4.583333
2  5501.954590  18.697226   8.978000  30.000002
3  7101.831055  17.357143   8.978000   0.000000
4  5235.987793  18.671329   9.080333  13.857677
```

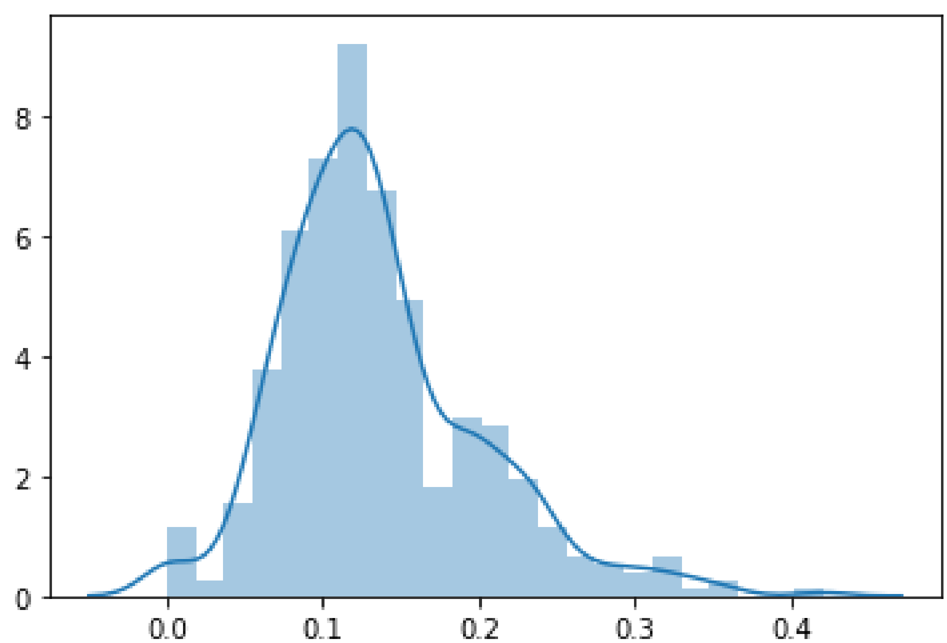
[5]:
```python
#Univariate Distribution: Test Scores
df_test = pd.DataFrame(ca_schools, columns=["testscr"])
df_test
sns.distplot(df_test)
```

[5]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d93e7374e0>
```



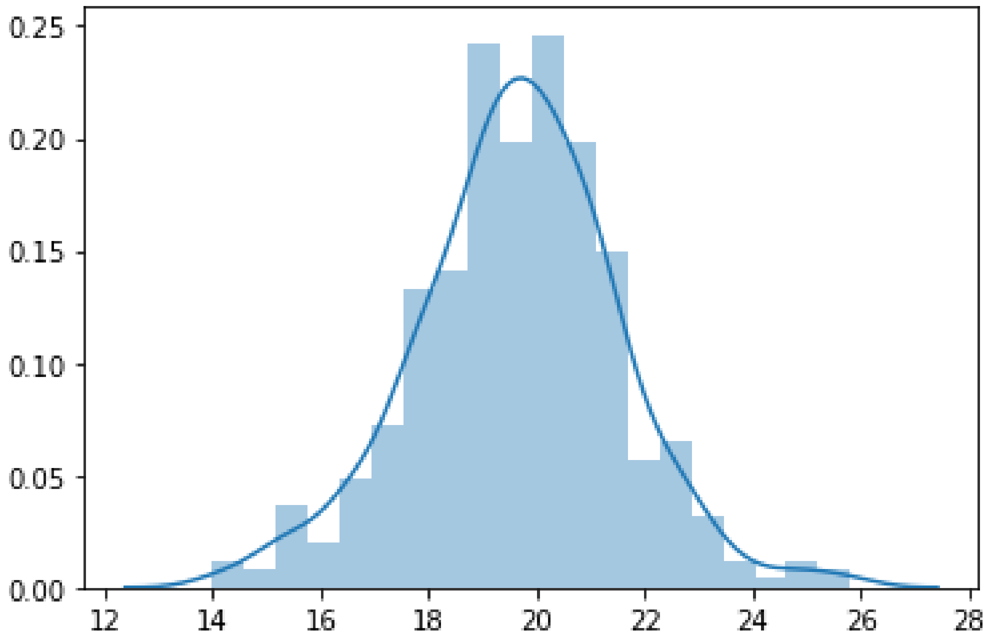
[6]:
```python
#Univariate Distribution: Computers Per Student
df_comp = pd.DataFrame(ca_schools, columns=["compstu"])
df_comp
sns.distplot(df_comp)
```

[6]: <matplotlib.axes._subplots.AxesSubplot at 0x1d93ea7af28>



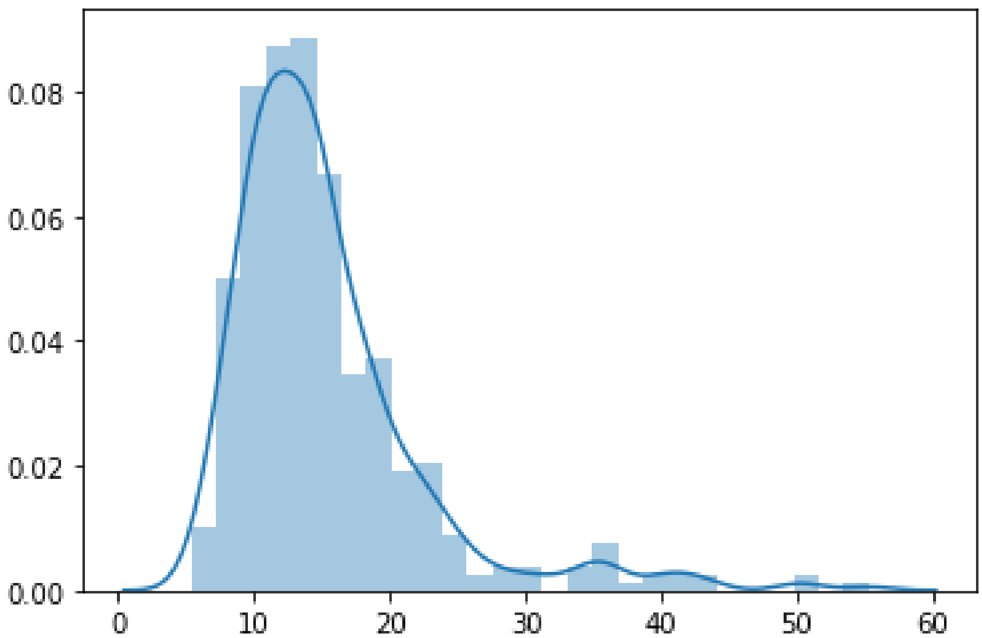
[7]:
```
#Univariate Distribution: Student/Teacher Ratio
df_str = pd.DataFrame(ca_schools, columns=["str"])
df_str
sns.distplot(df_str)
```

[7]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d93eb34390>
```



[8]:
```
#Univariate Distribution: Average Income
df_inc = pd.DataFrame(ca_schools, columns=["avginc"])
df_inc
sns.distplot(df_inc)
```

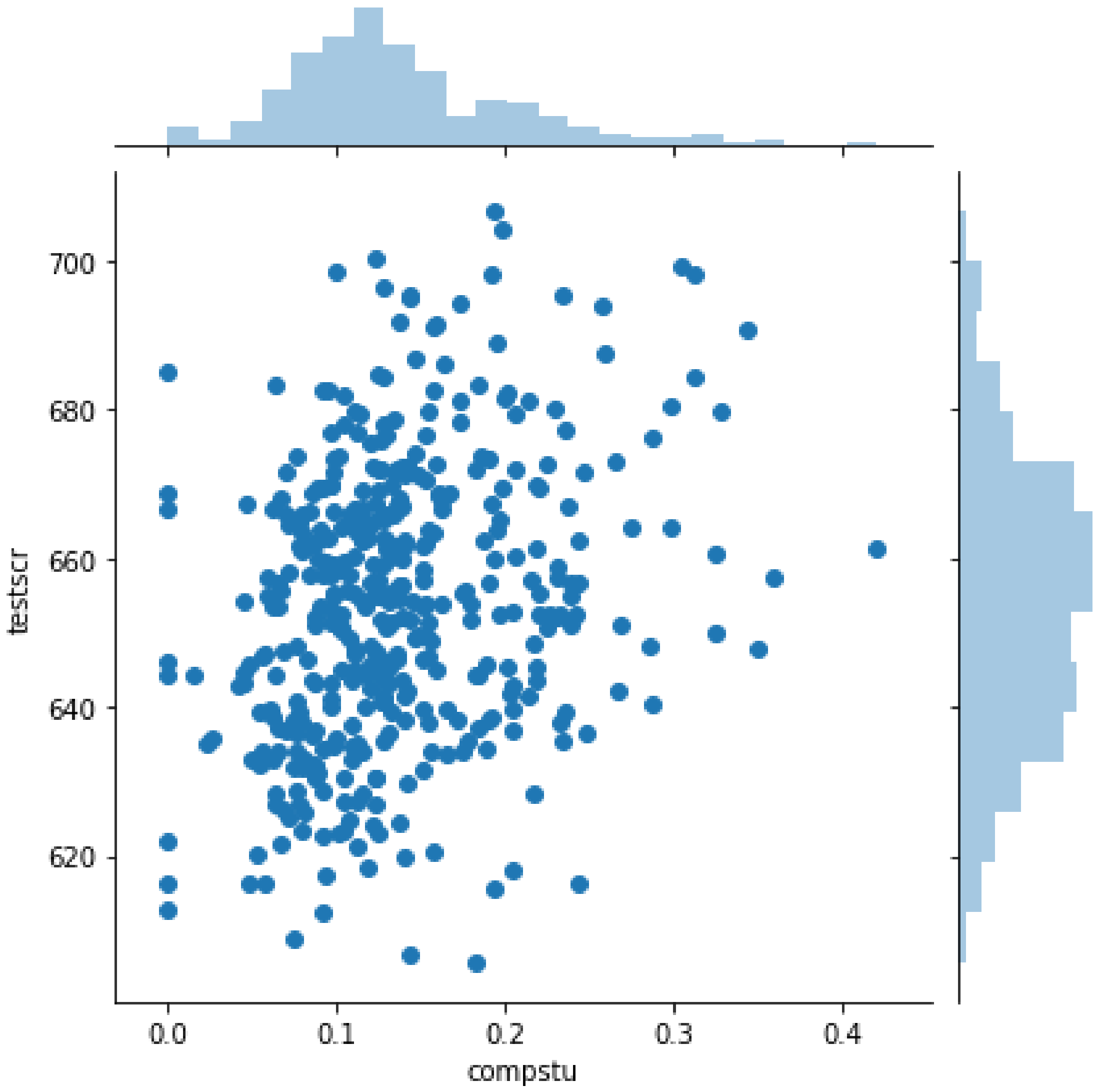
[8]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d93eb3cc50>
```



0.0.3 1.2 Visualize the dependency of the target on each feature from 1.1.

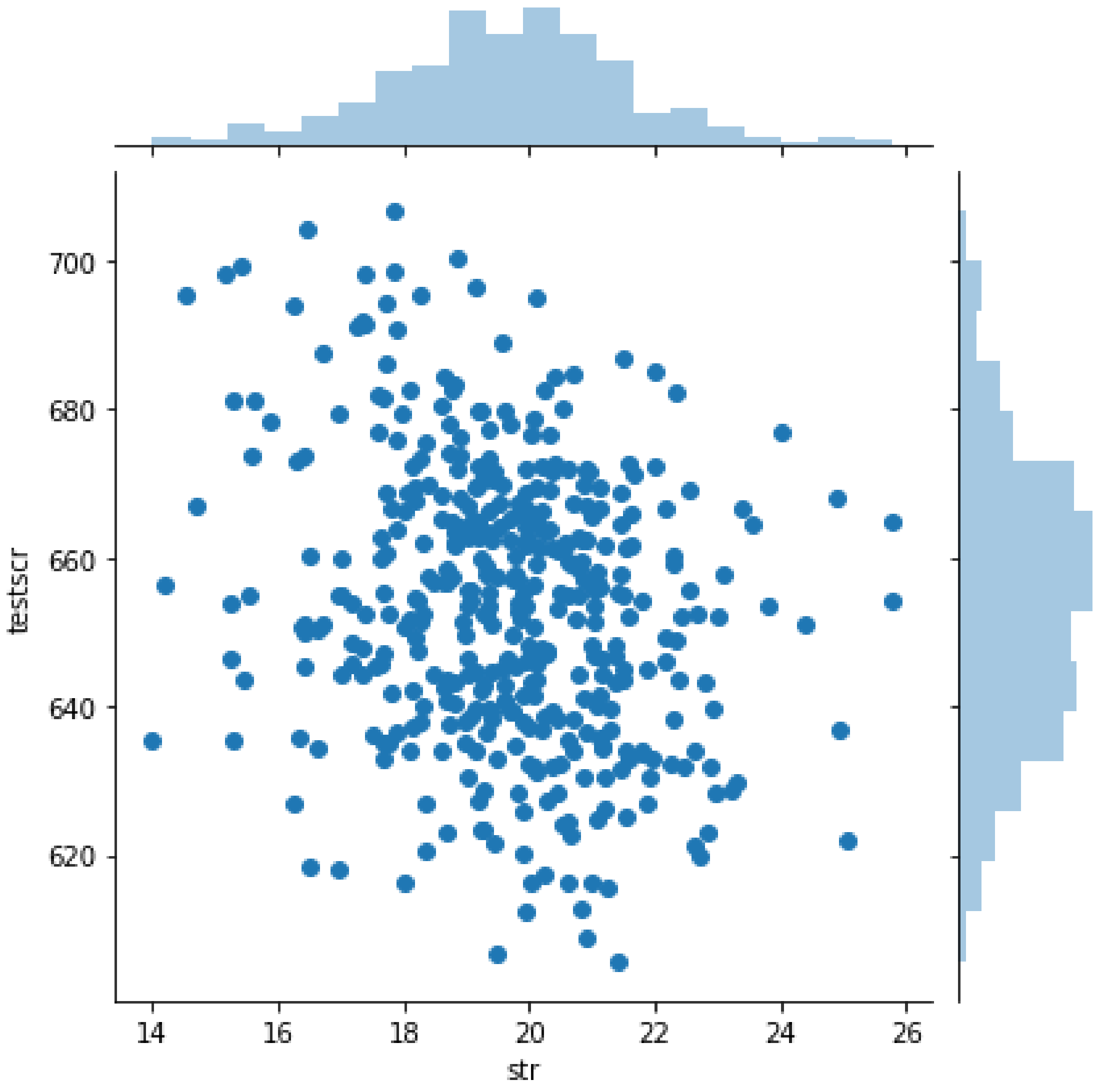
[9]:
```
sns.jointplot(x="compstu", y="testscr", data=ca_schools)
```

[9]: <seaborn.axisgrid.JointGrid at 0x1d93ec5b9e8>



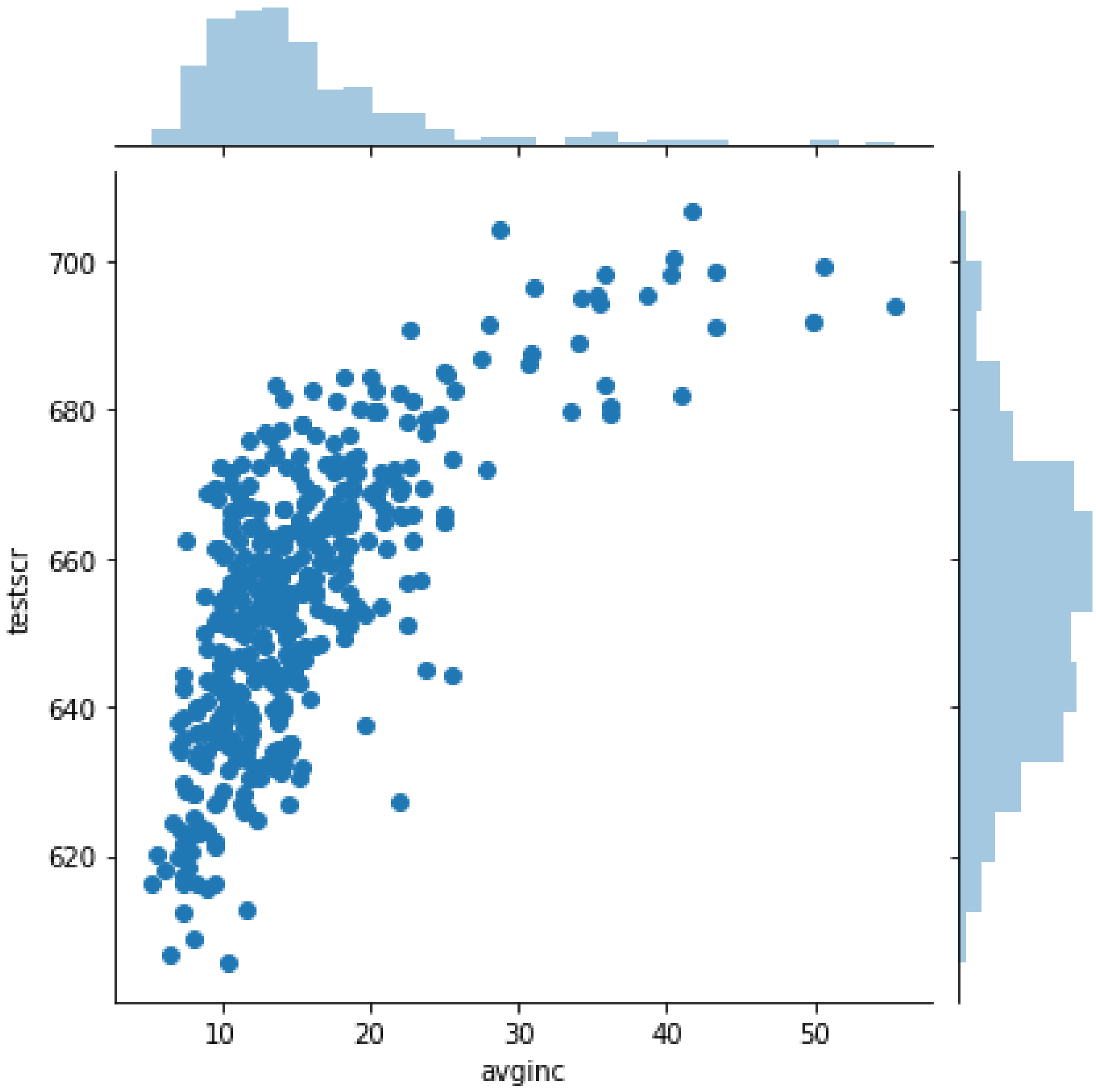
[10]:
```
sns.jointplot(x="str", y="testscr", data=ca_schools)
```

[10]: <seaborn.axisgrid.JointGrid at 0x1d93edc99e8>



[11]:
```
sns.jointplot(x="avginc", y="testscr", data=ca_schools)
```

[11]: `<seaborn.axisgrid.JointGrid at 0x1d93ef228d0>`



0.0.4 1.3 Split data in training and test set. Build models that evaluate the relationship between all available X variables in the California test dataset and the target variable. Evaluate KNN for regression, Linear Regression (OLS), Ridge, and Lasso using cross-validation with the default parameters. Does scaling the data with the StandardScaler help?

Split data in training and test set

[32]:
```
y = ca_schools['testscr']
y=y.astype("int64")
```

[33]:
```
X = ca_schools.drop(['Unnamed: 0', 'county', 'district','grspan','testscr'],␣
 ↪axis=1)
```

[34]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y)
```

[35]:
```
from sklearn import preprocessing
scaler = preprocessing.StandardScaler().fit(X_train)
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[16]:
```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import KFold

kfold = KFold(n_splits=5)
skfold = StratifiedKFold(n_splits=5, shuffle=True)
rkf = RepeatedKFold(n_splits=5, n_repeats=10)
```

0.0.5 KNN for Regression

[17]:
```
from sklearn.neighbors import KNeighborsRegressor

knn = KNeighborsRegressor(n_neighbors=5)
knn.fit(X_train, y_train)


print("R^2: {:.2f}".format(knn.score(X_test, y_test)))

y_pred = knn.predict(X_test)
```

```
R^2: 0.04
```

KNN for Regression w/ Scaled Data

[18]:
```
knn = KNeighborsRegressor(n_neighbors=5)
knn.fit(X_train_scaled, y_train)

print("R^2: {:.2f}".format(knn.score(X_test_scaled, y_test)))
```

```
R^2: 0.69
```

Scaling the data using the Standard Scalar, which standardizes by calculating a standard score. This score is calculated through the use of the following formula: z = (x-u)/s. Where z is the score, x is the unit to be standardized u is the mean of the data samples and s is their standard deviation. In the case of KNN Regression standardizing the data has produced a model with greater explanatory power, as we can see an increase in R^2 from 0.04 to 0.69 suggesting that when standardized 69% of the variation in y can be explained by x, where only 4% can be explained given no standardization.

Sources: 1. https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html 2. QMSSGR5073 'Preprocessing Data.ipynb', "Using StandardScaler()

KNN for Regression Cross Validation

[44]:
```
#Empty space in regressor assumes n_neighbors = 5

print("KFold Mean:\n{}".format(
cross_val_score(KNeighborsRegressor(), X, y, cv=kfold).mean()))

print("StratifiedKFold Mean:\n{}".format(
cross_val_score(KNeighborsRegressor(), X, y, cv=skfold).mean()))

print("RepeatedKFold Mean:\n{}".format(
cross_val_score(KNeighborsRegressor(), X, y, cv=rkf).mean()))
```

```
KFold Mean:
-16.071366760448093
StratifiedKFold Mean:
0.01232438589727749
RepeatedKFold Mean:
-0.017588968334293246
```

We see that when apply different types of cross-validation, holding the n_ neighbors constant, we get back some negative scores (these scores equate to the average R^2 for the runs of cross validation) Upon running the model with the test and train data the negatives went away, however no examples on scikit or the notes suggest using the split data. Found examples use the data as a whole separated by X (independent variables) and y (dependent variables). As a result, the previous cell was provided, despite the negative measure of R^2. Do note the stratified KFold mean is positive, which appears to suggest that we can get some small positive explanatory power by ensuring that each fold has the same proportion of observations.

Sources: 1. https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.cross_val_score.htm 2. QMSSGR5073 "Knn_CV_and_Model_Tuning.ipynb, 'Using Cross validation for model evaluation' "

3. https://towardsdatascience.com/cross-validation-explained-evaluating-estimator-performance-e51e5430ff85

0.0.6 Linear Regression (OLS)

[45]:
```
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
```

[46]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)
```

Linear Regression (OLS) w/ Non-Scaled Data

[47]:
```
lr = LinearRegression().fit(X_train, y_train)
```

[48]:
```
X_train_new = sm.add_constant(X_train)
model = sm.OLS(y_train, X_train_new ).fit()

model.summary()
```

[48]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                testscr   R-squared:                       0.805
Model:                            OLS   Adj. R-squared:                  0.799
Method:                 Least Squares   F-statistic:                     125.5
Date:                Mon, 02 Mar 2020   Prob (F-statistic):          1.24e-101
Time:                        11:32:12   Log-Likelihood:                -1099.0
No. Observations:                 315   AIC:                             2220.
Df Residuals:                     304   BIC:                             2261.
Df Model:                          10
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        663.1277     10.936     60.635      0.000     641.607     684.648
enrltot        0.0002      0.002      0.095      0.924      -0.003       0.004
teachers      -0.0080      0.038     -0.208      0.835      -0.083       0.067
calwpct       -0.1048      0.068     -1.542      0.124      -0.239       0.029
mealpct       -0.3639      0.042     -8.745      0.000      -0.446      -0.282
computer       0.0022      0.003      0.661      0.509      -0.004       0.009
compstu       -1.3673      8.528     -0.160      0.873     -18.149      15.415
expnstu        0.0019      0.001      1.911      0.057   -5.65e-05       0.004
str           -0.3460      0.367     -0.942      0.347      -1.069       0.377
avginc         0.5201      0.096      5.395      0.000       0.330       0.710
elpct         -0.1963      0.042     -4.681      0.000      -0.279      -0.114
==============================================================================
Omnibus:                        1.564   Durbin-Watson:                   1.873
Prob(Omnibus):                  0.457   Jarque-Bera (JB):                1.377
Skew:                           0.016   Prob(JB):                        0.502
Kurtosis:                       3.322   Cond. No.                     1.58e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.58e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

Linear Regression w/ Scaled Data

[49]:
```
X_train_new = sm.add_constant(X_train_scaled)
model = sm.OLS(y_train, X_train_new).fit()

model.summary()
```

[49]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                testscr   R-squared:                       0.009
Model:                            OLS   Adj. R-squared:                 -0.023
Method:                 Least Squares   F-statistic:                    0.2893
Date:                Mon, 02 Mar 2020   Prob (F-statistic):              0.983
Time:                        11:32:27   Log-Likelihood:                -1354.9
No. Observations:                 315   AIC:                             2732.
Df Residuals:                     304   BIC:                             2773.
Df Model:                          10
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        653.8063      1.024    638.376      0.000     651.791     655.822
x1             5.5483     15.980      0.347      0.729     -25.898      36.995
x2            -5.8866     17.138     -0.343      0.731     -39.610      27.837
x3            -0.1447      1.728     -0.084      0.933      -3.544       3.255
x4            -1.4030      2.539     -0.552      0.581      -6.400       3.594
x5             0.6326      3.486      0.181      0.856      -6.226       7.492
x6            -0.1151      1.241     -0.093      0.926      -2.557       2.326
x7             0.7187      1.429      0.503      0.615      -2.093       3.531
x8            -0.1529      1.539     -0.099      0.921      -3.182       2.876
x9            -1.3574      1.577     -0.861      0.390      -4.460       1.745
x10            1.8683      1.669      1.119      0.264      -1.417       5.153
==============================================================================
Omnibus:                        0.609   Durbin-Watson:                   1.892
Prob(Omnibus):                  0.737   Jarque-Bera (JB):                0.713
Skew:                           0.011   Prob(JB):                        0.700
Kurtosis:                       2.768   Cond. No.                         43.4
==============================================================================

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

In the case of Linear Regression, scaling the data has a negative impact on the explanatory power of the model. We see some changes in the size of the coefficients, and the decrease of t-stats, which suggest the variables should not be included in the model, as one cannot reject the null hypothesis that the independent variables explain nothing with regard to our y (dependent variable).

Linear Regression Cross Validation

[53]:
```
print("KFold:\n{}".format(
cross_val_score(LinearRegression(), X, y, cv=kfold).mean()))

print("StratifiedKFold:\n{}".format(
cross_val_score(LinearRegression(), X, y, cv=skfold).mean()))

print("RepeatedKFold:\n{}".format(
cross_val_score(LinearRegression(), X, y, cv=rkf).mean()))
```

```
KFold:
-4.379031971136683
StratifiedKFold:
0.80008382405661
RepeatedKFold:
0.7926505547400525
```

We see that when apply different types of cross-validation we get back a negative score from KFold. Cross Validation through Stratified Kfold and Repeated Kfold suggest that the independent variables in the linear regression can explain 80% of the variation in our dependent variable.

0.0.7 Ridge Regression

[54]:
```
from sklearn.linear_model import Ridge
from sklearn.linear_model import RidgeCV
```

Ridge Regression w/ Non-Scaled Data

[65]:
```
ridge = Ridge().fit(X_train, y_train)
print("Training R^2: {:.2f}".format(ridge.score(X_train, y_train)))
print("Test R^2: {:.2f}".format(ridge.score(X_test, y_test)))
```

```
Training R^2: 0.80
Test R^2: 0.81
```

Ridge Regression w/ Scaled Data

[62]:
```
scaler = preprocessing.StandardScaler()
scaler.fit(X_train)
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[64]:
```
ridge = Ridge().fit(X_train_scaled, y_train)
print("Training R^2: {:.2f}".format(ridge.score(X_train_scaled, y_train)))
print("Test R^2: {:.2f}".format(ridge.score(X_test_scaled, y_test)))
```

```
Training R^2: 0.80
Test R^2: 0.81
```

This ridge regression does not seem to experience a change in explanatory power given the scaled data.

Ridge Regression Cross Validaion

[66]:
```
print("KFold:\n{}".format(
cross_val_score(Ridge(), X, y, cv=kfold).mean()))

print("StratifiedKFold:\n{}".format(
cross_val_score(Ridge(), X, y, cv=skfold).mean()))

print("RepeatedKFold:\n{}".format(
cross_val_score(Ridge(), X, y, cv=rkf).mean()))
```

```
KFold:
-4.3006576536144925
StratifiedKFold:
0.8047688959618053
RepeatedKFold:
0.7917275577377194
```

We see that when apply different types of cross-validation we get back a negative score from KFold. Cross Validation through Stratified Kfold and Repeated Kfold suggest that the independent variables in the ridge regression can explain roughly 80% of the variation in our dependent variable.

0.0.8 Lasso Regression

Lasso Regression w/ Non-Scaled Data

[68]:
```
from sklearn.linear_model import Lasso
```

[69]:
```
lasso = Lasso().fit(X_train, y_train)
print("Training R^2: {:.2f}".format(lasso.score(X_train, y_train)))
print("Test R^2: {:.2f}".format(lasso.score(X_test, y_test)))
print("Number of features used: {}".format(np.sum(lasso.coef_ != 0)))
#print("lasso.coef_: {}".format(lasso.coef_))
```

```
Training R^2: 0.80
Test R^2: 0.81
Number of features used: 8
```

Lasso Regressoion w/ Scaled Data

[71]:
```
lasso = Lasso().fit(X_train_scaled, y_train)
print("Training R^2: {:.2f}".format(lasso.score(X_train_scaled, y_train)))
print("Test R^2: {:.2f}".format(lasso.score(X_test_scaled, y_test)))
print("Number of features used: {}".format(np.sum(lasso.coef_ != 0)))

#print("lasso.coef_: {}".format(lasso.coef_))
```

```
Training R^2: 0.80
Test R^2: 0.79
Number of features used: 5
```

This lasso regression seems to experience a change in explanatory power given the scaled data, but it is very small and negative. This change is only with regard to the explanatory power on the testing data.

Lasso Regression Cross Validation

[72]:
```
print("KFold:\n{}".format(
cross_val_score(Lasso(), X, y, cv=kfold).mean()))

print("StratifiedKFold:\n{}".format(
cross_val_score(Lasso(), X, y, cv=skfold).mean()))

print("RepeatedKFold:\n{}".format(
cross_val_score(Lasso(), X, y, cv=rkf).mean()))
```

```
KFold:
-4.28885690538308
StratifiedKFold:
0.8009257618920553
RepeatedKFold:
0.7937523019896281
```

We see that when apply different types of cross-validation we get back a negative score from KFold. Cross Validation through Stratified Kfold and Repeated Kfold suggest that the independent variables in the lasso regression can explain roughly 80% of the variation in our dependent variable.

0.0.9 1.4 Tune the parameters of the models where possible using GridSearchCV. Do the results improve?

[76]:
```
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
```

KNN GridSearch CV

[77]:
```
knn_pipe = make_pipeline(KNeighborsRegressor())
```

[80]:
```
param_grid = {'kneighborsregressor__n_neighbors': range(1, 10)}
grid = GridSearchCV(knn_pipe, param_grid, cv=10)
grid.fit(X_train, y_train)
print(grid.best_params_)
print(grid.best_score_)
```

```
{'kneighborsregressor__n_neighbors': 9}
-0.016257788001062312
```

[81]:
```
knn_pipe = make_pipeline(StandardScaler(), KNeighborsRegressor())
```

[82]:
```
param_grid = {'kneighborsregressor__n_neighbors': range(1, 10)}
grid = GridSearchCV(knn_pipe, param_grid, cv=10)
grid.fit(X_train, y_train)
print(grid.best_params_)
print(grid.best_score_)
```

```
{'kneighborsregressor__n_neighbors': 7}
0.7172474999397614
```

GridSearch CV appears to suggest that for the KNN regressor benefits from scaling, as the R^2 has become positive. the ideal n_neighbors would be 7 and this would produce a model with an explanatory power of 0.717, which suggests that 72% of the variation in y (dependent variable) can be explained by x (independent variables)

Ridge Regression GridSearch CV

[83]:
```
ridge_pipe = make_pipeline(Ridge())
```

[84]:
```
param_grid = {'ridge__alpha': [0.01, 0.1, 1, 10, 100,1000,10000]}
grid = GridSearchCV(ridge_pipe, param_grid, cv=10)
grid.fit(X_train, y_train)
print(grid.best_params_)
print(grid.best_score_)
```

```
{'ridge__alpha': 1000}
0.7822304800155856
```

[85]:
```
ridge_pipe = make_pipeline(StandardScaler(), Ridge())
```

[86]:
```
param_grid = {'ridge__alpha': [0.01, 0.1, 1, 10, 100,1000,10000]}
grid = GridSearchCV(ridge_pipe, param_grid, cv=10)
grid.fit(X_train, y_train)
print(grid.best_params_)
print(grid.best_score_)
```

```
{'ridge__alpha': 10}
0.7828517182362517
```

Our grid search seems to suggest that the best model will have an alpha of 1000 with unscaled data and 10 with scaled data. This appears to make sense because as the model's alpha approaches 0 the model begins to become increasingly similar to an OLS regression. So for data that is unscaled a larger alpha makes sense as it requires more of a smoothness constraint to find explanatory power. The scaled data can operate more like an OLS because the variation in the data has been standardized, thus making it simpler for the OLS to predict.

[92]:
```
ridge10 = Ridge(alpha=10).fit(X_train, y_train)
print("Training R^2: {:.2f}".format(ridge10.score(X_train, y_train)))
print("Test set R^2: {:.2f}".format(ridge10.score(X_test, y_test)))
```

```
Training R^2: 0.80
Test set R^2: 0.81
```

[91]:
```
ridge1000 = Ridge(alpha=1000).fit(X_train_scaled, y_train)
print("Training R^2: {:.2f}".format(ridge1000.score(X_train_scaled, y_train)))
print("Test set R^2: {:.2f}".format(ridge1000.score(X_test_scaled, y_test)))
```

```
Training R^2: 0.56
Test set R^2: 0.52
```

Lasso Regression GridSearch CV

[93]:
```
lasso_pipe = make_pipeline(Lasso())
```

[94]:
```
param_grid = {'lasso__alpha': [0.01, 0.1, 1, 10, 100,1000,10000]}
grid = GridSearchCV(lasso_pipe, param_grid, cv=10)
grid.fit(X_train, y_train)
print(grid.best_params_)
print(grid.best_score_)
```

```
{'lasso__alpha': 1}
0.7823411438316094
```

[95]:
```
lasso_pipe = make_pipeline(StandardScaler(), Lasso())
```

[96]:
```
param_grid = {'lasso__alpha': [0.01, 0.1, 1, 10, 100,1000,10000]}
grid = GridSearchCV(lasso_pipe, param_grid, cv=10)
grid.fit(X_train, y_train)
print(grid.best_params_)
print(grid.score(X_test, y_test))
```

```
{'lasso__alpha': 0.1}
0.806544494469053
```

With regard to lasso, our grid search seems to suggest that the best model will have an alpha of 1 with unscaled data and 0.1 with scaled data. This appears to make sense because as the model's alpha approaches 0 the model begins to become increasingly similar to an OLS regression, but as alpha becomes to large coefficients will begin to 0 out. It is not surprising then that we see much lower alpha measures for lasso than for ridge while keeping a similar level of explanatory power.

[98]:
```
lasso01 = Lasso(alpha=0.1).fit(X_train, y_train)
print("Training R^2: {:.2f}".format(lasso01.score(X_train, y_train)))
print("Test R^2: {:.2f}".format(lasso01.score(X_test, y_test)))
```

```
Training R^2: 0.80
Test R^2: 0.81
```

[105]:
```
int(lasso.score(X_test, y_test))
print(lasso.coef_)
```

```
[ -0.          -0.          -0.         -10.6393318   -0.
   0.           0.46691845  -0.19918508   3.34742122  -2.53863698]
```

One can see from the basic lasso coefficients that the previously mentioned zeroing out has occured.

0.0.10 1.5 Compare the coefficients of your two best linear models (not knn), do they agree on which features are important?

[103]:
```
print(ridge10.score(X_test, y_test))
print(ridge10.coef_)
```

```
0.8088485493057405
[ 1.18796341e-04 -6.54095365e-03 -1.03943211e-01 -3.64516588e-01
  1.93892193e-03 -1.09733165e-01  1.88222319e-03 -3.30166182e-01
  5.18872011e-01 -1.95405911e-01]
```

[104]:
```
print(lr.score(X_test, y_test))
print(lr.coef_)
```

```
0.8081674788950314
[ 1.64271449e-04 -7.97874165e-03 -1.04839109e-01 -3.63865590e-01
  2.15309332e-03 -1.36726004e+00  1.88904899e-03 -3.45970527e-01
  5.20091618e-01 -1.96277441e-01]
```

The models provided above have similar explanatory power, suggesting that their best models will provide an R^2 value near .80 which suggests that 80% of the variation in our dependent variable can be explained by our independent variables. We also can see that while the magnitude of the coefficients has changed slight from one model to the next, the signs stay the same, this is good as the models don't contradict the explanatory nature of the features within them. Realizing similar scores across different types of regressions is promising, as it suggests that the data does have the ability to explain the dependent variables variation in a variety of settings.

0.0.11 1.6 Discuss which final model you would choose to predict new data

I would choose the ridge regression having gone through the analysis so far. The ridge regression leverages the L2 penalty which makes it more challenging to discover a signal by adding "a value equal to the square of the magnitude of coefficients" to the model. Ridge also allows a parsimonious model to be created despite the presence of multicollinarity, while this HW does not discuss multicollinarity, if I were doing research I would certainly consider a model that had strong explanatory power while also having mitigated the potential risk of finding multicollinarity.

Sources: 1. https://www.statisticshowto.datasciencecentral.com/ridge-regression/ 2. https://www.statisticshowto.datasciencecentral.com/regularization/

0.0.12 Question 2

First, import the red and the white wine csv files into separate pandas dataframes from the following website:

https://archive.ics.uci.edu/ml/machine-learning-databases/wine-quality

(Note: you need to adjust the argument for read_csv() from sep=',' to sep=';')

Add a new column to each data frame called "winetype". For the white wine dataset label the values in this column with a 0, indicating white wine. For the red wine dataset, label values with a 1, indicating red wine. Combine both datasets into a single dataframe.

The target data (i.e. the dependent variable) is "winetype".

[3]:
```
import pandas as pd
```

[106]:
```
red_wine = pd.read_csv("D:/QMSS/Spring/Machine Learning/winequality-red.
 ↪csv",sep=';')
white_wine = pd.read_csv("D:/QMSS/Spring/Machine Learning/winequality-white.
 ↪csv",sep=';')
```

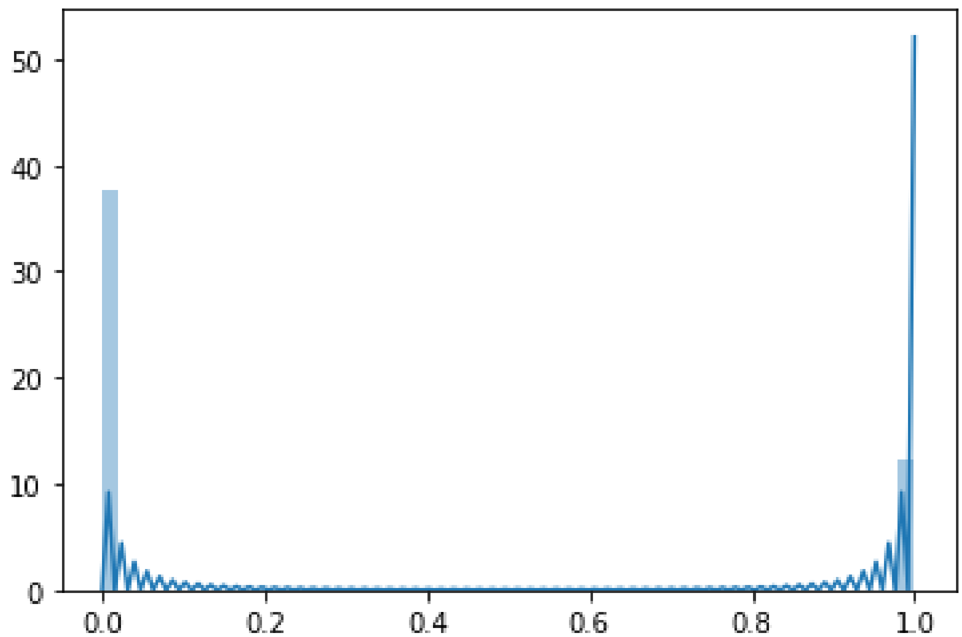
[107]:
```
red_wine['winetype'] = 1
white_wine['winetype'] = 0
frames = [red_wine, white_wine]
wines = pd.concat(frames)
wines.head()
```

[107]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.4              0.70         0.00             1.9      0.076
1            7.8              0.88         0.00             2.6      0.098
2            7.8              0.76         0.04             2.3      0.092
3           11.2              0.28         0.56             1.9      0.075
4            7.4              0.70         0.00             1.9      0.076

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56
1                 25.0                  67.0   0.9968  3.20       0.68
2                 15.0                  54.0   0.9970  3.26       0.65
3                 17.0                  60.0   0.9980  3.16       0.58
4                 11.0                  34.0   0.9978  3.51       0.56

   alcohol  quality  winetype
0      9.4        5         1
1      9.8        5         1
2      9.8        5         1
3      9.8        6         1
4      9.4        5         1
```

0.0.13 2.1 Visualize the univariate distribution of the target feature and each of the three explanatory variables that you think are likely to have a relationship with the target feature.

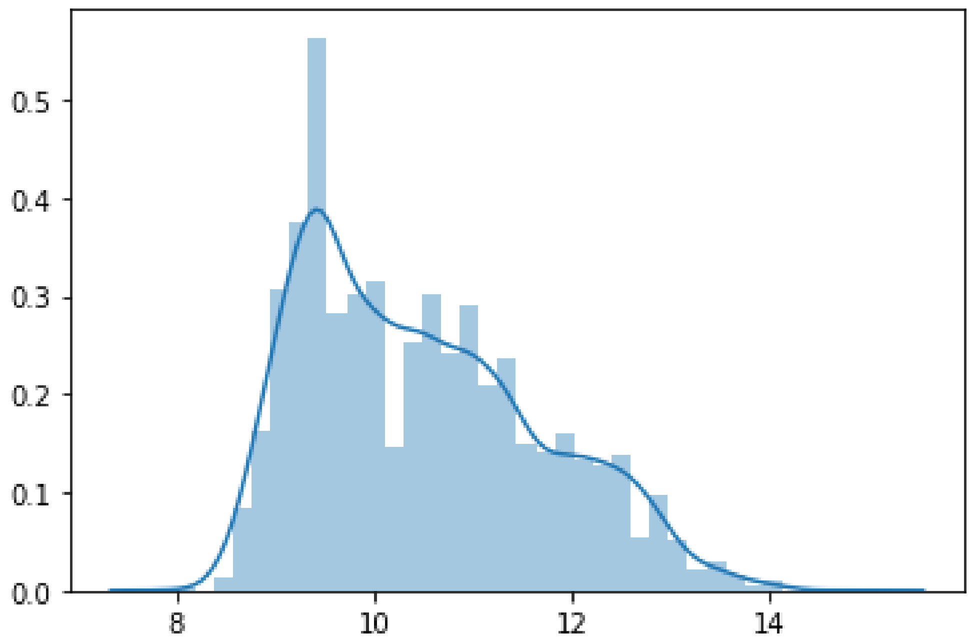
[108]:
```
#Univariate Distribution Wine Types
wine_type = pd.DataFrame(wines, columns=["winetype"])
sns.distplot(wine_type)
```

[108]: `<matplotlib.axes._subplots.AxesSubplot at 0x1d9427479e8>`



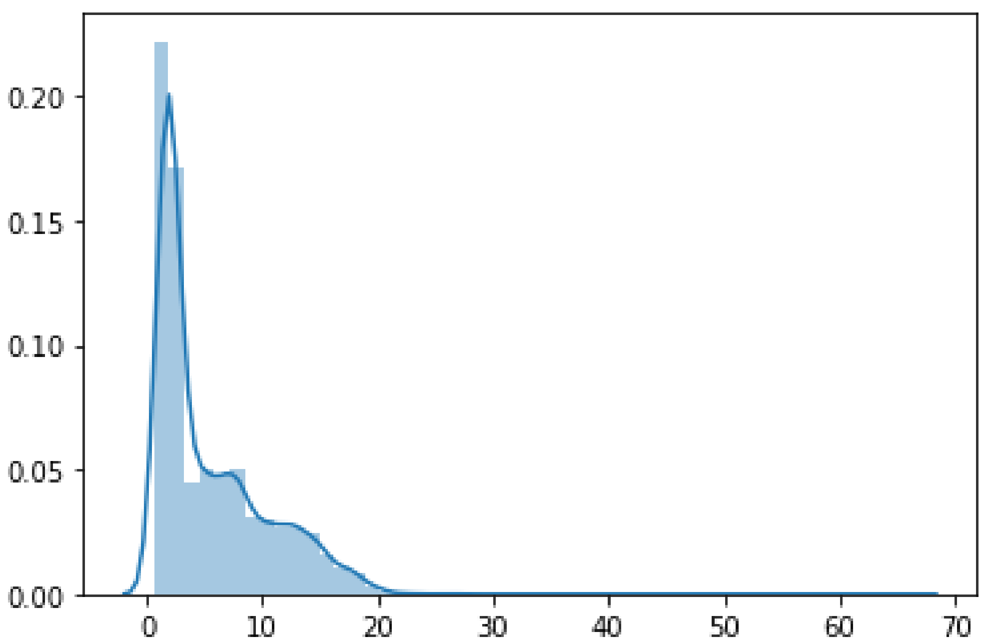
[109]:
```
#Univariate Distribution: Alcohol Content by Percentage
alcohol = pd.DataFrame(wines, columns=["alcohol"])
sns.distplot(alcohol)
```

[109]: `<matplotlib.axes._subplots.AxesSubplot at 0x1d93f9cc1d0>`



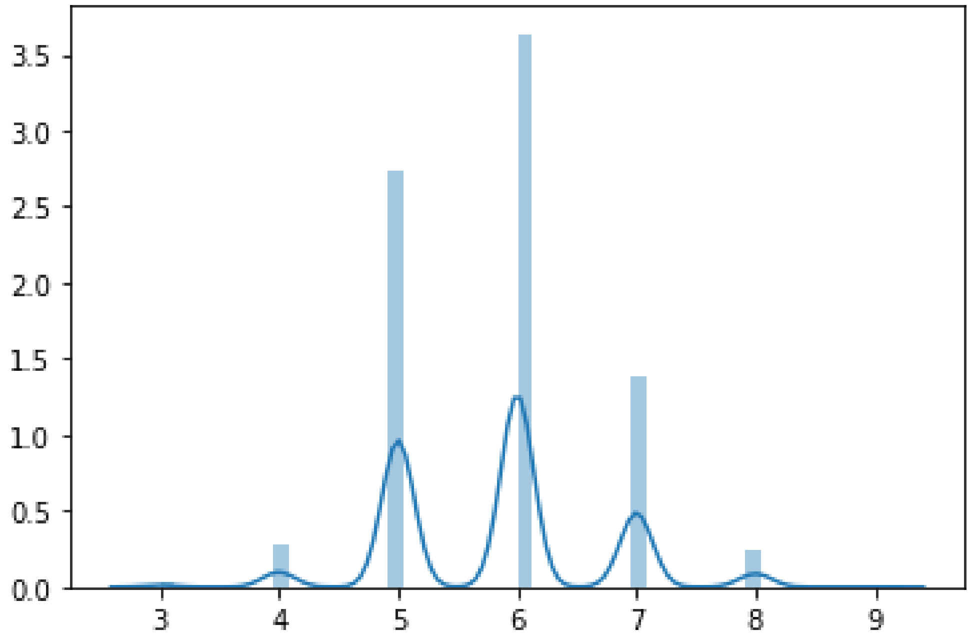
[110]:
```
#Univariate Distribution: Sugar Content
sugar = pd.DataFrame(wines, columns=["residual sugar"])
sns.distplot(sugar)
```

[110]: <matplotlib.axes._subplots.AxesSubplot at 0x1d942897f98>



[111]:
```
#Univariate Distribution: Quality Rating
quality = pd.DataFrame(wines, columns=["quality"])
sns.distplot(quality)
```

[111]: <matplotlib.axes._subplots.AxesSubplot at 0x1d94298ad30>



0.0.14 2.2 Split data into training and test set. Build models that evaluate the relationship between all available X variables in the dataset and the target variable. Evaluate Logistic Regression, Penalized Logistic Regression, and KNN for classification using cross-validation. How different are the results? How does scaling the data with StandardScaler influence the results?

[112]:
```
y = wines['winetype']
X = wines.loc[:, wines.columns!="winetype"]
```

[113]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y)
```

[114]:
```
#from sklearn import preprocessing
scaler = preprocessing.StandardScaler().fit(X_train)
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

KNN for Classification w/ Non-Scaled Data

[115]:
```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=5)
```

```
knn.fit(X_train, y_train)

print("accuracy: {:.2f}".format(knn.score(X_test, y_test)))

y_pred = knn.predict(X_test) # y_pred includes your predictions
```

```
accuracy: 0.94
```

KNN for Classification w/ Scaled Data

[116]:
```
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train_scaled, y_train)

print("accuracy: {:.2f}".format(knn.score(X_test_scaled, y_test)))

y_pred = knn.predict(X_test_scaled)
```

```
accuracy: 0.99
```

We see that for KNN Classification, scaling the data has made produced a model that has stronger predictive power, with classification accuracy increasing from 0.94 to 0.99.

Cross Validation for KNN Classification

[118]:
```
print("KFold:\n{}".format(
cross_val_score(KNeighborsClassifier(), X, y, cv=kfold).mean()))

print("StratifiedKFold:\n{}".format(
cross_val_score(KNeighborsClassifier(n_neighbors=5), X, y, cv=skfold).mean()))

print("RepeatedKFold:\n{}".format(
cross_val_score(KNeighborsClassifier(n_neighbors=5), X, y, cv=rkf).mean()))
```

```
KFold:
0.9089049564753953
StratifiedKFold:
0.9435133419704602
RepeatedKFold:
0.942158429561201
```

We see that when cross validating, using a variety of different approaches, we are still receiving measure that show strong classification abilities with all means being greater than 0.9.

0.0.15 Logistic Regression

[119]:
```
from sklearn.linear_model import LogisticRegression
```

Logistic Regression w/ Non-Scaled Data

[120]:
```
logreg = LogisticRegression(C=1e90).fit(X_train, y_train)
```

[121]:
```
import statsmodels.api as sm

X_train_new = sm.add_constant(X_train)

model = sm.GLM(y_train, X_train_new, family=sm.families.Binomial()).fit()

model.summary()
```

[121]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:               winetype   No. Observations:                 4872
Model:                            GLM   Df Residuals:                     4859
Model Family:                Binomial   Df Model:                           12
Link Function:                  logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -168.26
Date:                Mon, 02 Mar 2020   Deviance:                       336.53
Time:                        13:03:59   Pearson chi2:                 1.16e+07
No. Iterations:                    10
Covariance Type:            nonrobust
================================================================================
========
                           coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
--------
const                -1643.1565    205.302     -8.004      0.000   -2045.540
-1240.773
fixed acidity           -0.0882      0.264     -0.334      0.739      -0.606
0.430
volatile acidity         7.6527      1.254      6.103      0.000       5.195
10.110
citric acid             -2.0395      1.281     -1.592      0.111      -4.551
0.472
residual sugar          -0.9643      0.115     -8.416      0.000      -1.189
-0.740
chlorides               21.0194      4.453      4.720      0.000      12.292
29.747
free sulfur dioxide      0.0675      0.015      4.442      0.000       0.038
0.097
total sulfur dioxide    -0.0512      0.006     -9.183      0.000      -0.062
-0.040
density               1636.5619    209.430      7.814      0.000    1226.086
2047.038
pH                      -0.8112      1.597     -0.508      0.612      -3.942
```

```
2.319
sulphates              3.1885      1.420      2.245      0.025       0.405
5.972
alcohol                1.5839      0.306      5.177      0.000       0.984
2.184
quality                0.3365      0.218      1.542      0.123      -0.091
0.764
================================================================================
========
"""
```

[129]:
```
print("Training Pseudo R^2: {:.3f}".format(logreg.score(X_train, y_train)))
print("Test Pseudo R^2: {:.3f}".format(logreg.score(X_test, y_test)))
```

```
Training Pseudo R^2: 0.989
Test Pseudo R^2: 0.988
```

Logistic Regression w/ Scaled Data

[125]:
```
logregsc = LogisticRegression(C=1e90).fit(X_train_scaled, y_train)
```

[126]:
```
X_train_new = sm.add_constant(X_train_scaled) #adding a column of 1s to the␣
 ↪matrix

model = sm.GLM(y_train, X_train_new, family=sm.families.Binomial()).fit()

model.summary()
```

[126]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:               winetype   No. Observations:                 4872
Model:                            GLM   Df Residuals:                     4859
Model Family:                Binomial   Df Model:                           12
Link Function:                  logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -168.26
Date:                Mon, 02 Mar 2020   Deviance:                       336.53
Time:                        13:07:06   Pearson chi2:                 1.16e+07
No. Iterations:                    10
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -4.2940      0.332    -12.921      0.000      -4.945      -3.643
x1            -0.1133      0.340     -0.334      0.739      -0.779       0.552
x2             1.2588      0.206      6.103      0.000       0.855       1.663
x3            -0.2957      0.186     -1.592      0.111      -0.660       0.068
x4            -4.6024      0.547     -8.416      0.000      -5.674      -3.531
```

```
x5              0.7126      0.151      4.720      0.000       0.417       1.009
x6              1.2129      0.273      4.442      0.000       0.678       1.748
x7             -2.8843      0.314     -9.183      0.000      -3.500      -2.269
x8              4.9373      0.632      7.814      0.000       3.699       6.176
x9             -0.1304      0.257     -0.508      0.612      -0.634       0.373
x10             0.4657      0.207      2.245      0.025       0.059       0.872
x11             1.8882      0.365      5.177      0.000       1.173       2.603
x12             0.2923      0.190      1.542      0.123      -0.079       0.664
==============================================================================
"""
```

[128]:
```
print("Training Pseudo R^2: {:.3f}".format(logregsc.score(X_train_scaled,␣
    ↪y_train)))
print("Test Pseudo R^2: {:.3f}".format(logregsc.score(X_test_scaled, y_test)))
```

```
Training Pseudo R^2: 0.994
Test Pseudo R^2: 0.995
```

We can see that for logistic regression scaling the data has produced a model that has slightly increased explanatory power, with the independent variables being able to explain 99% of the variation in y. Our previous model could explain just under 99%.

Logistic Regression Cross Validation

[130]:
```
print("KFold:\n{}".format(
cross_val_score(LogisticRegression(C=1e90), X, y, cv=kfold).mean()))

print("StratifiedKFold:\n{}".format(
cross_val_score(LogisticRegression(C=1e90), X, y, cv=skfold).mean()))

print("RepeatedKFold:\n{}".format(
cross_val_score(LogisticRegression(C=1e90), X, y, cv=rkf).mean()))
```

```
KFold:
0.981072777876473
StratifiedKFold:
0.9881478036322833
RepeatedKFold:
0.9883638064783561
```

We see that when cross validating, using a variety of different approaches, we are still receiving measure that show strong predicative abilities with all means being greater than 0.98.

0.0.16 Penalized Logistic Regression

Penalized Logistic Regression w/ Non-Scaled Data

[131]:
```
lgr1 = LogisticRegression(C=1e90, penalty = 'l1').fit(X_train, y_train)
```

[132]:
```
print("Training Pseudo R^2: {:.3f}".format(lgr1.score(X_train, y_train)))
print("Test Pseudo R^2: {:.3f}".format(lgr1.score(X_test, y_test)))
```

```
Training Pseudo R^2: 0.989
Test Pseudo R^2: 0.985
```

[150]:
```
lgr2 = LogisticRegression(C=1e90, penalty = 'l2').fit(X_train, y_train)
```

[151]:
```
print("Training Pseudo R^2: {:.3f}".format(lgr2.score(X_train, y_train)))
print("Test Pseudo R^2: {:.3f}".format(lgr2.score(X_test, y_test)))
```

```
Training Pseudo R^2: 0.989
Test Pseudo R^2: 0.988
```

Penalized Logistic Regression w/ Scaled Data

[152]:
```
lgr1 = LogisticRegression(C=1e90, penalty = 'l1').fit(X_train_scaled, y_train)
```

[153]:
```
print("Training Pseudo R^2: {:.3f}".format(lgr1.score(X_train_scaled, y_train)))
print("Test Pseudo R^2: {:.3f}".format(lgr1.score(X_test_scaled, y_test)))
```

```
Training Pseudo R^2: 0.994
Test Pseudo R^2: 0.995
```

[155]:
```
lgr2 = LogisticRegression(C=1e90, penalty = 'l2').fit(X_train_scaled, y_train)
```

[156]:
```
print("Training Pseudo R^2: {:.3f}".format(lgr2.score(X_train_scaled, y_train)))
print("Test Pseudo R^2: {:.3f}".format(lgr2.score(X_test_scaled, y_test)))
```

```
Training Pseudo R^2: 0.994
Test Pseudo R^2: 0.995
```

We can see that for penalized logistic regression scaling the data has produced a model that has slightly increased explanatory power, with the independent variables being able to explain 99% of the variation in y. Our previous model could explain just under 99%.

Penalized Logistic Regression Cross Validation (l1 Penalty)

[139]:
```
print("KFold:\n{}".format(
cross_val_score(LogisticRegression(C=1e90,penalty="l1"), X, y, cv=kfold).
 ↪mean()))

print("StratifiedKFold:\n{}".format(
cross_val_score(LogisticRegression(C=1e90,penalty="l1"), X, y, cv=skfold).
 ↪mean()))

print("RepeatedKFold:\n{}".format(
cross_val_score(LogisticRegression(C=1e90,penalty="l1"), X, y, cv=rkf).mean()))
```

```
KFold:
0.9807650855687807
StratifiedKFold:
0.9870704062707037
RepeatedKFold:
0.9879790963463019
```

Penalized Logistic Regression Cross Validation (l2 Penalty)

[140]:
```python
print("KFold:\n{}".format(
cross_val_score(LogisticRegression(C=1e90,penalty="l2"), X, y, cv=kfold).
 ↪mean()))

print("StratifiedKFold:\n{}".format(
cross_val_score(LogisticRegression(C=1e90,penalty="l2"), X, y, cv=skfold).
 ↪mean()))

print("RepeatedKFold:\n{}".format(
cross_val_score(LogisticRegression(C=1e90,penalty="l2"), X, y, cv=rkf).mean()))
```

```
KFold:
0.981072777876473
StratifiedKFold:
0.9878404657150497
RepeatedKFold:
0.9882564576301297
```

We see that when accounting for penalty, cross validating, using a variety of different approaches, we are still receiving measure that show strong predicative abilities with all means being greater than 0.98.

0.0.17 2.3 Tune the parameters where possible using GridSearchCV. Do the results improve?

Logistic Regression w/ GridSearch CV

[178]:
```python
lgr = LogisticRegression()

penalty = ['l1', 'l2']


C = np.logspace(0, 4, 10)


hyperparameters = dict(C=C, penalty=penalty)
```

Logistic Regression w/ GridSearch CV Non-Scaled Data

[142]:
```python
#grid = GridSearchCV(lgr, param_grid, cv=10, scoring = 'accuracy', )
grid = GridSearchCV(lgr, param_grid=hyperparameters, cv=10)
```

```
grid_sc = GridSearchCV(lgr, param_grid=hyperparameters, cv=10)
```

[ ]:

[143]:
```
grid.fit(X_train, y_train)
```

[143]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='warn',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='warn',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'C': array([1.00000000e+00, 2.78255940e+00,
7.74263683e+00, 2.15443469e+01,
       5.99484250e+01, 1.66810054e+02, 4.64158883e+02, 1.29154967e+03,
       3.59381366e+03, 1.00000000e+04]),
                         'penalty': ['l1', 'l2']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[144]:
```
print("Pseudo R^2: {:.3f}".format(grid.score(X_test, y_test)))
print('Best Penalty:', grid.best_estimator_.get_params()['penalty'])
print('Best C:', grid.best_estimator_.get_params()['C'])
```

```
test-set score: 0.986
Best Penalty: l2
Best C: 59.94842503189409
```

[145]:
```
print("KFold:\n{}".format(
cross_val_score(LogisticRegression(C=59.94842503189409,penalty="l2"), X, y,␣
 ↪cv=kfold).mean()))

print("StratifiedKFold:\n{}".format(
cross_val_score(LogisticRegression(C=59.94842503189409,penalty="l2"), X, y,␣
 ↪cv=skfold).mean()))

print("RepeatedKFold:\n{}".format(
cross_val_score(LogisticRegression(C=59.94842503189409,penalty="l2"), X, y,␣
 ↪cv=rkf).mean()))
```

```
KFold:
0.974611120980636
StratifiedKFold:
0.9879953786900199
```

```
RepeatedKFold:
0.9878561141706639
```

Logistic Regression w/ GridSearch CV w/ Scaled Data

[146]:
```
grid_sc.fit(X_train_scaled, y_train)
```

[146]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='warn',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='warn',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'C': array([1.00000000e+00, 2.78255940e+00,
7.74263683e+00, 2.15443469e+01,
       5.99484250e+01, 1.66810054e+02, 4.64158883e+02, 1.29154967e+03,
       3.59381366e+03, 1.00000000e+04]),
                         'penalty': ['l1', 'l2']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[157]:
```
print("Pseudo R^2: {:.3f}".format(grid_sc.score(X_test_scaled, y_test)))
print('Best Penalty:', grid_sc.best_estimator_.get_params()['penalty'])
print('Best C:', grid_sc.best_estimator_.get_params()['C'])
```

```
Pseudo R^2: 0.995
Best Penalty: l1
Best C: 7.742636826811269
```

[158]:
```
print("KFold:\n{}".format(
cross_val_score(LogisticRegression(C=7.742636826811269,penalty="l1"), X, y,␣
 ↪cv=kfold).mean()))

print("StratifiedKFold:\n{}".format(
cross_val_score(LogisticRegression(C=7.742636826811269,penalty="l1"), X, y,␣
 ↪cv=skfold).mean()))

print("RepeatedKFold:\n{}".format(
cross_val_score(LogisticRegression(C=7.742636826811269,penalty="l1"), X, y,␣
 ↪cv=rkf).mean()))
```

```
KFold:
0.9792262687274235
StratifiedKFold:
```

```
0.9878401105946415
RepeatedKFold:
0.9878560904838042
```

Having performed GridSearch with respect to both penalty type and C value we were able to discover the best approach for logistic regressions with both scaled and not scaled data. The models we discovered, whose ability to predict, can be measured using the pseudo R^2 term predict similarly to previous models but has shown a slight improvement

0.0.18 2.4 Change the cross-validation strategy in GridSearchCV from 'stratified k-fold' to 'kfold' with shuffling. Do the parameters for models that can be tuned change? Do they change if you change the random seed of the shuffling? Or if you change the random state of the split into training and test data?

KFold w/ Shuffle False

[159]:
```
grid = GridSearchCV(lgr, param_grid=hyperparameters, cv=KFold(shuffle=False,␣
↪random_state=124238920380932))
grid_sc = GridSearchCV(lgr, param_grid=hyperparameters, cv=KFold(shuffle=False,␣
↪random_state=124238920380932))
```

[160]:
```
grid.fit(X_train, y_train)
```

[160]:
```
GridSearchCV(cv=KFold(n_splits=3, random_state=124238920380932, shuffle=False),
             error_score='raise-deprecating',
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='warn',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='warn',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'C': array([1.00000000e+00, 2.78255940e+00,
7.74263683e+00, 2.15443469e+01,
       5.99484250e+01, 1.66810054e+02, 4.64158883e+02, 1.29154967e+03,
       3.59381366e+03, 1.00000000e+04]),
                         'penalty': ['l1', 'l2']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[161]:
```
print("Pseudo R^2: {:.3f}".format(grid.score(X_test, y_test)))
print('Best Penalty:', grid.best_estimator_.get_params()['penalty'])
print('Best C:', grid.best_estimator_.get_params()['C'])
```

```
Pseudo R^2: 0.988
Best Penalty: l1
Best C: 166.81005372000593
```

[162]:
```
grid_sc.fit(X_train_scaled, y_train)
```

[162]:
```
GridSearchCV(cv=KFold(n_splits=3, random_state=124238920380932, shuffle=False),
             error_score='raise-deprecating',
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='warn',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='warn',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'C': array([1.00000000e+00, 2.78255940e+00,
7.74263683e+00, 2.15443469e+01,
       5.99484250e+01, 1.66810054e+02, 4.64158883e+02, 1.29154967e+03,
       3.59381366e+03, 1.00000000e+04]),
                         'penalty': ['l1', 'l2']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[163]:
```
print("Pseudo R^2: {:.3f}".format(grid_sc.score(X_test_scaled, y_test)))
print('Best Penalty:', grid_sc.best_estimator_.get_params()['penalty'])
print('Best C:', grid_sc.best_estimator_.get_params()['C'])
```

```
Pseudo R^2: 0.994
Best Penalty: l1
Best C: 2.7825594022071245
```

KFold w/ Shuffle True

[164]:
```
grid = GridSearchCV(lgr, param_grid=hyperparameters, cv=KFold(shuffle=True,␣
↪random_state=1242389203))
grid_sc = GridSearchCV(lgr, param_grid=hyperparameters, cv=KFold(shuffle=True,␣
↪random_state=1242389203))
```

[165]:
```
grid.fit(X_train, y_train)
```

[165]:
```
GridSearchCV(cv=KFold(n_splits=3, random_state=1242389203, shuffle=True),
             error_score='raise-deprecating',
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='warn',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='warn',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'C': array([1.00000000e+00, 2.78255940e+00,
```

```
7.74263683e+00, 2.15443469e+01,
       5.99484250e+01, 1.66810054e+02, 4.64158883e+02, 1.29154967e+03,
       3.59381366e+03, 1.00000000e+04]),
                         'penalty': ['l1', 'l2']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[166]:
```
print("Pseudo R^2: {:.3f}".format(grid.score(X_test, y_test)))
print('Best Penalty:', grid.best_estimator_.get_params()['penalty'])
print('Best C:', grid.best_estimator_.get_params()['C'])
```

```
Pseudo R^2: 0.987
Best Penalty: l2
Best C: 1291.5496650148827
```

[167]:
```
grid_sc.fit(X_train_scaled, y_train)
```

[167]:
```
GridSearchCV(cv=KFold(n_splits=3, random_state=1242389203, shuffle=True),
             error_score='raise-deprecating',
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='warn',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='warn',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'C': array([1.00000000e+00, 2.78255940e+00,
7.74263683e+00, 2.15443469e+01,
       5.99484250e+01, 1.66810054e+02, 4.64158883e+02, 1.29154967e+03,
       3.59381366e+03, 1.00000000e+04]),
                         'penalty': ['l1', 'l2']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[168]:
```
print("Pseudo R^2: {:.3f}".format(grid_sc.score(X_test_scaled, y_test)))
print('Best Penalty:', grid_sc.best_estimator_.get_params()['penalty'])
print('Best C:', grid_sc.best_estimator_.get_params()['C'])
```

```
Pseudo R^2: 0.994
Best Penalty: l2
Best C: 2.7825594022071245
```

KFold w/ New Seed

[169]:
```
grid = GridSearchCV(lgr, param_grid=hyperparameters, cv=KFold(shuffle=True,␣
↪random_state=45))
```

```
grid_sc = GridSearchCV(lgr, param_grid=hyperparameters, cv=KFold(shuffle=True,␣
↪random_state=45))
```

[170]:
```
grid.fit(X_train, y_train)
```

[170]:
```
GridSearchCV(cv=KFold(n_splits=3, random_state=45, shuffle=True),
             error_score='raise-deprecating',
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='warn',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='warn',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'C': array([1.00000000e+00, 2.78255940e+00,
7.74263683e+00, 2.15443469e+01,
       5.99484250e+01, 1.66810054e+02, 4.64158883e+02, 1.29154967e+03,
       3.59381366e+03, 1.00000000e+04]),
                         'penalty': ['l1', 'l2']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[171]:
```
print("Pseudo R^2: {:.3f}".format(grid.score(X_test, y_test)))
print('Best Penalty:', grid.best_estimator_.get_params()['penalty'])
print('Best C:', grid.best_estimator_.get_params()['C'])
```

```
Pseudo R^2: 0.987
Best Penalty: l2
Best C: 464.15888336127773
```

[172]:
```
grid_sc.fit(X_train_scaled, y_train)
```

[172]:
```
GridSearchCV(cv=KFold(n_splits=3, random_state=45, shuffle=True),
             error_score='raise-deprecating',
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='warn',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='warn',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'C': array([1.00000000e+00, 2.78255940e+00,
7.74263683e+00, 2.15443469e+01,
       5.99484250e+01, 1.66810054e+02, 4.64158883e+02, 1.29154967e+03,
       3.59381366e+03, 1.00000000e+04]),
```

```
                        'penalty': ['l1', 'l2']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[173]:
```
print("Pseudo R^2: {:.3f}".format(grid_sc.score(X_test_scaled, y_test)))
print('Best Penalty:', grid_sc.best_estimator_.get_params()['penalty'])
print('Best C:', grid_sc.best_estimator_.get_params()['C'])
```

```
Pseudo R^2: 0.995
Best Penalty: l1
Best C: 1.0
```

KFold w/ New Seed and Shuffle off

[174]:
```
grid = GridSearchCV(lgr, param_grid=hyperparameters, cv=KFold(shuffle=False,␣
 ↪random_state=45))
grid_sc = GridSearchCV(lgr, param_grid=hyperparameters, cv=KFold(shuffle=False,␣
 ↪random_state=45))
```

[175]:
```
grid.fit(X_train, y_train)
```

[175]:
```
GridSearchCV(cv=KFold(n_splits=3, random_state=45, shuffle=False),
             error_score='raise-deprecating',
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='warn',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='warn',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'C': array([1.00000000e+00, 2.78255940e+00,
7.74263683e+00, 2.15443469e+01,
       5.99484250e+01, 1.66810054e+02, 4.64158883e+02, 1.29154967e+03,
       3.59381366e+03, 1.00000000e+04]),
                         'penalty': ['l1', 'l2']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[473]:
```
print("Pseudo R^2: {:.3f}".format(grid.score(X_test, y_test)))
print('Best Penalty:', grid.best_estimator_.get_params()['penalty'])
print('Best C:', grid.best_estimator_.get_params()['C'])
```

```
test-set score: 0.985
Best Penalty: l1
Best C: 21.544346900318832
```

[176]:
```
grid_sc.fit(X_train_scaled, y_train)
```

[176]:
```
GridSearchCV(cv=KFold(n_splits=3, random_state=45, shuffle=False),
             error_score='raise-deprecating',
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='warn',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='warn',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'C': array([1.00000000e+00, 2.78255940e+00,
7.74263683e+00, 2.15443469e+01,
       5.99484250e+01, 1.66810054e+02, 4.64158883e+02, 1.29154967e+03,
       3.59381366e+03, 1.00000000e+04]),
                         'penalty': ['l1', 'l2']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[177]:
```python
print("Pseudo R^2: {:.3f}".format(grid_sc.score(X_test_scaled, y_test)))
print('Best Penalty:', grid_sc.best_estimator_.get_params()['penalty'])
print('Best C:', grid_sc.best_estimator_.get_params()['C'])
```

```
Pseudo R^2: 0.994
Best Penalty: l1
Best C: 2.7825594022071245
```

R^2

Not Scaled, Scaled 1. KFold w/ Shuffle False -> .989,.994 2. KFold w/ Shuffle True -> .987, .994 3. KFold w/ New Seed -> .987,.995 4. KFold w/ New Seed and Shuffle off -> .995, .994

We see that with this data there does not seem to be much change in explanatory power given the adjustments of the see and shuffling. The odd one out of the bunch appears to be 4. which is the only rendition where the not scaled data performed better than the scaled, however the difference is minimal.

0.0.19 2.5 Lastly, compare the coefficients for Logistic Regression and Penalized Logistic Regression and discuss which final model you would choose to predict new data.

[179]:
```python
print(lgr1.score(X_test, y_test))
print(lgr1.coef_)
```

```
0.7366153846153846
[[-0.10555434  1.26078425 -0.29515375 -4.58857718  0.71340921  1.21073104
  -2.88390237  4.91817648 -0.12439965  0.46839067  1.8779795   0.29223981]]
```

[180]:
```python
print(lgr2.score(X_test, y_test))
print(lgr2.coef_)
```

```
0.7366153846153846
[[-0.11178505  1.25809256 -0.29652698 -4.59653572  0.71280629  1.21350348
  -2.88391744  4.93460978 -0.13016557  0.46576363  1.88780997  0.29192203]]
```

[181]:
```python
print(logreg.score(X_test, y_test))
print(logreg.coef_)
```

```
0.9876923076923076
[[ 1.41487490e+00  1.17570208e+01 -8.64211847e-01 -1.13141558e-01
   3.19822777e+01  5.31743334e-02 -6.25925503e-02 -1.99751713e+01
   8.91778445e+00  8.59114984e+00 -3.20166513e-01  2.14757181e-03]]
```

I would be inclined to use the penalized logistic regressions in this case because seldom is a model found with a R^2 so near to 1 that has no underlying issues. Multicollinearity may be at play in the non-penalized logistic regression, and this could be inspiring an artificially high R^2 value, because of this, I would inclined to reference the penalized models, as they account for multicollinearity, and have R^2 values that suggest that there may be additional features that could explain some of the variation in y, which is are more likely occurrence then having found all the independent features (x) that can explain the variation of the dependent variable (y).