Assignment1

March 1, 2018

```
In [1]: import pandas as pd
        import matplotlib.pyplot as plt
        import numpy as np
        from sklearn import datasets, linear_model
        from sklearn.cross_validation import train_test_split
        from sklearn.datasets import make_blobs
        from sklearn.preprocessing import PolynomialFeatures, StandardScaler
        import seaborn
        seaborn.set()
```

```
/usr/local/lib/python3.5/dist-packages/sklearn/cross_validation.py:41: DeprecationWarning: This
  "This module will be removed in 0.20.", DeprecationWarning)
```

1 2 Linear Regression

1.1 2.1 Explore Raw Dataset

1.1.1 2.1.1 Read the raw data with pandas.read_csv()

```
In [2]: df = pd.read_csv('imports-85.data',
                         header=None,
                         names=['Symboling', 'Losses', 'Make', 'Fuel_Type', 'Aspiration', 'Num_o
                                'Body_Style', 'Drive_Wheels', 'Engine_Location', 'Wheel_Base', '
                                'Width', 'Height', 'Curb_Weight', 'Engine_Type', 'Num_of_Cylinde
                                'Engine_Size', 'Fuel_System', 'Bore', 'Stroke', 'Compression_Rat
                                'Horsepower', 'Peak_rpm', 'City_mpg', 'Highway_mpg', 'Price'],
                         na_values=('?'))
```

```
In [3]: df.head(3)
```

```
Out[3]:    Symboling  Losses         Make Fuel_Type Aspiration Num_of_Doors  \
        0          3     NaN  alfa-romero       gas        std          two
        1          3     NaN  alfa-romero       gas        std          two
        2          1     NaN  alfa-romero       gas        std          two

            Body_Style Drive_Wheels Engine_Location  Wheel_Base    ...     Engine_Size  \
        0  convertible          rwd           front        88.6    ...             130
```

```
1  convertible          rwd           front        88.6   ...             130
2    hatchback          rwd           front        94.5   ...             152

   Fuel_System  Bore  Stroke Compression_Ratio Horsepower  Peak_rpm City_mpg  \
0         mpfi  3.47    2.68               9.0      111.0    5000.0       21
1         mpfi  3.47    2.68               9.0      111.0    5000.0       21
2         mpfi  2.68    3.47               9.0      154.0    5000.0       19

   Highway_mpg    Price
0           27  13495.0
1           27  16500.0
2           26  16500.0

[3 rows x 26 columns]
```

In [4]:
```
df.isnull().sum()[df.isnull().sum() != 0]
```

Out[4]:
```
Losses          41
Num_of_Doors     2
Bore             4
Stroke           4
Horsepower       2
Peak_rpm         2
Price            4
dtype: int64
```

1.1.2 2.1.2 Data cleaning: remove the data sample with missing values

In [5]:
```
df.dropna(axis=0, how='any', inplace=True)
```

1.1.3 2.1.3 Data Standardization

In [6]:
```
split_idx = int(df.shape[0] * .2)
df_train, df_test = df[split_idx:], df[:split_idx]
```

In [7]:
```
engine_size_stdscaler = StandardScaler()
df_train.loc[:, 'Std_Engine_Size'] = engine_size_stdscaler.fit_transform(
    df_train.Engine_Size.values.reshape(-1, 1))
df_test.loc[:, 'Std_Engine_Size'] = engine_size_stdscaler.transform(
    df_test.Engine_Size.values.reshape(-1, 1))
price_stdscaler = StandardScaler()
df_train.loc[:, 'Std_Price'] = price_stdscaler.fit_transform(
    df_train.Price.values.reshape(-1, 1))
df_test.loc[:, 'Std_Price'] = price_stdscaler.transform(
    df_test.Price.values.reshape(-1, 1))
horsepower_stdscaler = StandardScaler()
df_train.loc[:, 'Std_Horsepower'] = horsepower_stdscaler.fit_transform(
    df_train.Horsepower.values.reshape(-1, 1))
df_test.loc[:, 'Std_Horsepower'] = horsepower_stdscaler.transform(
    df_test.Horsepower.values.reshape(-1, 1))
```

```
/usr/local/lib/python3.5/dist-packages/sklearn/utils/validation.py:475: DataConversionWarning: D
  warnings.warn(msg, DataConversionWarning)
/usr/local/lib/python3.5/dist-packages/pandas/core/indexing.py:357: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self.obj[key] = _infer_fill_value(value)
/usr/local/lib/python3.5/dist-packages/pandas/core/indexing.py:537: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self.obj[item] = s
```

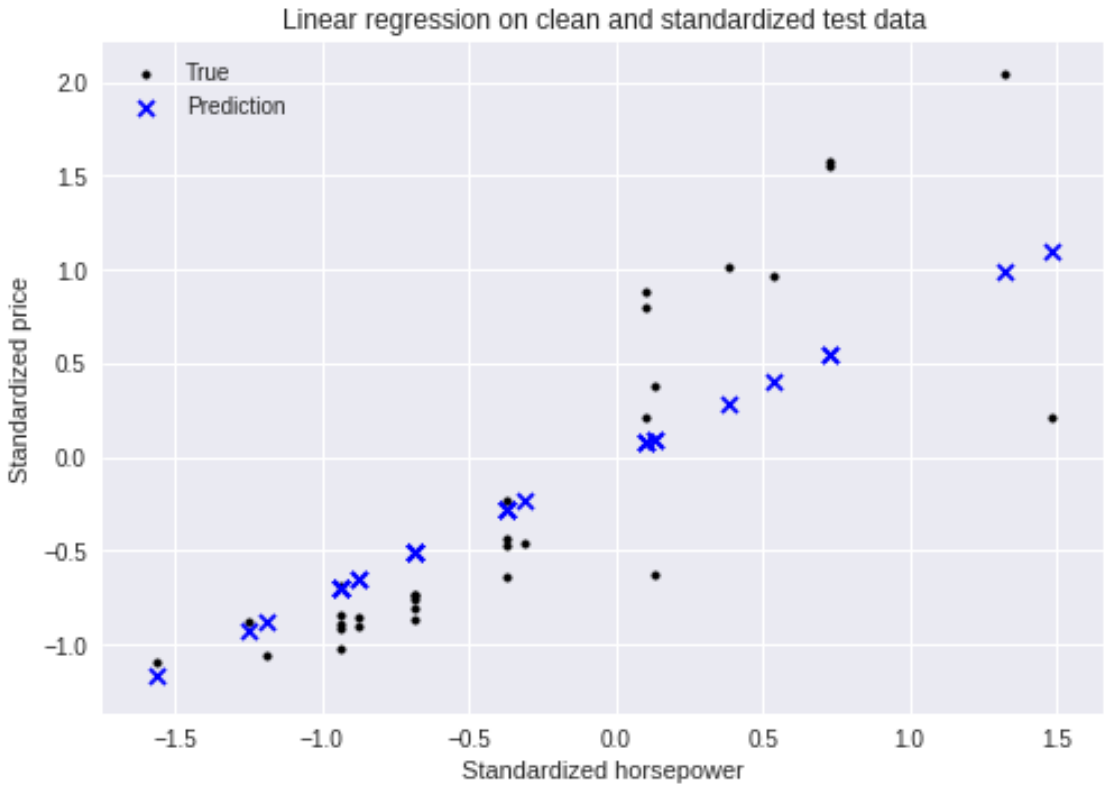
```
In [8]: X_train, X_test, y_train, y_test = df_train['Std_Horsepower'], df_test[
            'Std_Horsepower'], df_train['Std_Price'], df_test['Std_Price']
```

1.1.4 2.1.4 Linear regression on the preprocessed data

```
In [9]: lin_reg = linear_model.LinearRegression().fit(
            X_train.values.reshape(-1, 1), y_train)

In [10]: lin_reg.score(X_train.values.reshape(-1, 1), y_train)

Out[10]: 0.551814313382951

In [11]: test_pred = lin_reg.predict(X_test.values.reshape(-1, 1))
```

Figure 1: Linear regression on clean and standardized test data

```
In [12]: true = plt.scatter(X_test, y_test, c='k', marker='.')
         pred = plt.scatter(X_test, test_pred, c='b', marker='x')
         plt.legend([true, pred], ['True', 'Prediction'])
         plt.xlabel('Standardized horsepower')
         plt.ylabel('Standardized price')
         plt.title('Linear regression on clean and standardized test data')

Out[12]: <matplotlib.text.Text at 0x7f37754a8ac8>

In [13]: plt.show()
```



1.2 2.2 Linear regression with multiple features

```
In [14]: Xm_train, ym_train = df[['Engine_Size', 'Horsepower', 'Peak_rpm']], df['Price']
```

```
In [15]: engine_size_stdscaler = StandardScaler()
         Xm_train.loc[:, 'Std_Engine_Size'] = engine_size_stdscaler.fit_transform(
             Xm_train.Engine_Size.values.reshape(-1, 1))
         horsepower_stdscaler = StandardScaler()
         Xm_train.loc[:, 'Std_Horsepower'] = horsepower_stdscaler.fit_transform(
             Xm_train.Horsepower.values.reshape(-1, 1))
         peak_rpm_stdscaler = StandardScaler()
         Xm_train.loc[:, 'Std_Peak_rpm'] = peak_rpm_stdscaler.fit_transform(
             Xm_train.Peak_rpm.values.reshape(-1, 1))
         price_stdscaler = StandardScaler()
         ym_train = price_stdscaler.fit_transform(ym_train.values.reshape(-1, 1))
```

```
/usr/local/lib/python3.5/dist-packages/sklearn/utils/validation.py:475: DataConversionWarning: D
  warnings.warn(msg, DataConversionWarning)
/usr/local/lib/python3.5/dist-packages/pandas/core/indexing.py:357: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self.obj[key] = _infer_fill_value(value)
/usr/local/lib/python3.5/dist-packages/pandas/core/indexing.py:537: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self.obj[item] = s
```

1.2.1 Solve multiple linear regression with normal equation.

```
In [16]: X_matrix = Xm_train[['Std_Horsepower',
                              'Std_Engine_Size', 'Std_Peak_rpm']].values
         bias_vector = np.ones((X_matrix.shape[0], 1))
         X_unit = np.append(bias_vector, X_matrix, axis=1)

In [17]: X_unit_t = np.transpose(X_unit)
         theta = np.dot(np.dot(np.linalg.inv(
             np.dot(X_unit_t, X_unit)), X_unit_t), ym_train)
```

Add scripts to lr_mfeature.py to print out the calculated theta with the following format:

```
In [18]: print('Parameter theta calculate by normal equation: (%.4f, %.4f, %.4f, %.4f)' %
               (theta[0][0], theta[1][0], theta[2][0], theta[3][0]))

Parameter theta calculate by normal equation: (0.0000, 0.2260, 0.6575, -0.0015)
```

1.2.2 Solve multiple linear regression with gradient descent.

Without changing the parameters:

```
In [19]: sgd_reg = linear_model.SGDRegressor(loss='squared_loss').fit(
             X_matrix, ym_train.reshape(ym_train.shape[0],))

/usr/local/lib/python3.5/dist-packages/sklearn/linear_model/stochastic_gradient.py:128: FutureWa
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

Add scripts to lr_mfeature.py to print out the calculated theta with the following format:

```
In [20]: print('Parameter theta calculated by SGD: (%.4f, %.4f, %.4f, %.4f)' %
               (sgd_reg.intercept_[0], sgd_reg.coef_[0], sgd_reg.coef_[1], sgd_reg.coef_[2]))

Parameter theta calculated by SGD: (0.0001, 0.3746, 0.4775, -0.0681)
```

With changing the parmaters: The under model is turned off l2_penalty and increased the iteration.

```
In [21]: sgd_reg_tuned = linear_model.SGDRegressor(loss='squared_loss', penalty='none', max_iter
             X_matrix, ym_train.reshape(ym_train.shape[0],))

In [22]: print('Parameter theta calculated by SGD: (%.4f, %.4f, %.4f, %.4f)' %
               (sgd_reg_tuned.intercept_[0], sgd_reg_tuned.coef_[0], sgd_reg_tuned.coef_[1], sgd

Parameter theta calculated by SGD: (0.0000, 0.2260, 0.6576, -0.0015)
```

Benchmark model by sklearn:

```
In [23]: lin_reg_bm = linear_model.LinearRegression().fit(X_matrix, ym_train)

In [24]: print('Parameter theta calculate by Sklearn: (%.4f, %.4f, %.4f, %.4f)' %
               (lin_reg_bm.intercept_[0], lin_reg_bm.coef_[0][0], lin_reg_bm.coef_[0][1], lin_re

Parameter theta calculate by Sklearn: (0.0000, 0.2260, 0.6575, -0.0015)
```

1.3 2.3 Polynomial Regression with Regularization

1.3.1 2.3.1 Polynomial regression on training data

```
In [25]: X_train = [[5.3], [7.2], [10.5], [14.7], [18], [20]]
         y_train = [[7.5], [9.1], [13.2], [17.5], [19.3], [19.5]]

In [26]: X_test = [[6], [8], [11], [22]]
         y_test = [[8.3], [12.5], [15.4], [19.6]]

In [27]: poly = PolynomialFeatures(degree=5, include_bias=False) #order 5 feature constructor
         X_train_poly = poly.fit_transform(X_train)
         X_test_poly = poly.transform(X_test)

In [28]: poly_reg = linear_model.LinearRegression().fit(X_train_poly, y_train)
```

Fill in the blank of the regression equation below

```
In [29]: print('y1 = %.4f + %.4f x + %.4f x*x + %.4f x*x*x + %.4f x*x*x*x + %.4f x*x*x*x*x' %
               (poly_reg.intercept_[0], poly_reg.coef_[0][0], poly_reg.coef_[0][1], poly_reg.coe

y1 = 18.2339 + -6.0512 x + 1.1119 x*x + -0.0799 x*x*x + 0.0027 x*x*x*x + -0.0000 x*x*x*x*x
```

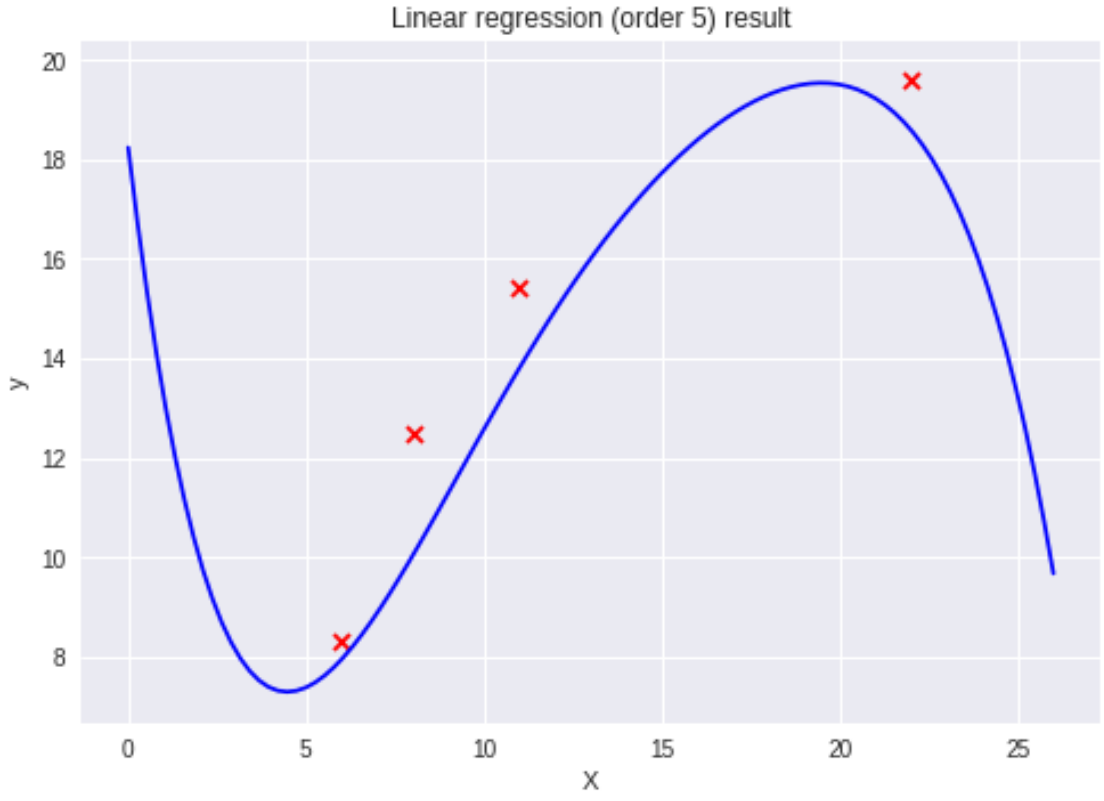
Add scripts to poly_regular.py to print the score of the linear regression model on the test data in the following format:

```
In [30]: print('Linear regression (order 5) score is: ', poly_reg.score(X_test_poly, y_test))

Linear regression (order 5) score is:  0.8567469916481851
```

```
In [31]: xx = np.linspace(0, 26, 100)
         xx_poly = poly.transform(xx.reshape(xx.shape[0], 1))
         yy_poly = poly_reg.predict(xx_poly)
```

Add script to poly_regular.py to plot the predicted output yy_poly versus xx, and also the test data (y_test versus X_test) in the same plot.

```
In [32]: plt.plot(xx, yy_poly, c='b')
         plt.scatter(X_test, y_test, c='r', marker='x')
         plt.xlabel('X')
         plt.ylabel('y')
         plt.title('Linear regression (order 5) result')
         plt.show()
```



1.3.2 2.3.2 Ridge Regression (with regularization)

```
In [33]: ridge_model = linear_model.Ridge(alpha=1., normalize=False)
         ridge_model.fit(X_train_poly, y_train)

Out[33]: Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
            normalize=False, random_state=None, solver='auto', tol=0.001)
```

Fill in the blank of the regression equation below

```
In [34]: print('y1 = %.4f + %.4f x + %.4f x*x + %.4f x*x*x + %.4f x*x*x*x + %.4f x*x*x*x*x' %
               (ridge_model.intercept_[0], ridge_model.coef_[0][0], ridge_model.coef_[0][1], rid

y1 = 5.7687 + -0.0029 x + 0.0124 x*x + 0.0143 x*x*x + -0.0011 x*x*x*x + 0.0000 x*x*x*x*x
```

Add scripts to poly_regular.py to print the score of the linear regression model on the test data in the following format:

```
In [35]: print('Ridge regression (order 5) score is: ', ridge_model.score(X_test_poly, y_test))

Ridge regression (order 5) score is:  0.8706689045767595
```

```
In [36]: yy_ridge = ridge_model.predict(xx_poly)
```

Add script to poly_regular.py to plot the predicted output yy_poly versus xx, and also the test data (y_test versus X_test) in the same plot.

```
In [37]: plt.plot(xx, yy_ridge, c='b')
         plt.scatter(X_test, y_test, c='r', marker='x')
         plt.xlabel('X')
         plt.ylabel('y')
         plt.title('Ridge regression (order 5) result')
         plt.show()
```

1.3.3 Benchmark (simple linear regression):

```
In [38]: benchmark = linear_model.LinearRegression().fit(X_train, y_train)

In [39]: print('Linear regression score is: ', benchmark.score(X_test, y_test))

Linear regression score is:  0.7175894154356046
```

1.3.4 2.3.3 Comparisions

Q1. Which model has the highest score? Ridge regression (the score is 0.8706).

Q2. Does a larger alpha result in a larger coefficient for x^5 in the regression equation in Ridge model (order 5)? No, the coefficient for x^5 is nearly zero.

2 3 Linear Discrimination / Classification

```
In [40]: n_samples = 10000

         centers = [(-1, -1), (1, 1)]
```

```
        X, y = make_blobs(n_samples=n_samples, n_features=2, cluster_std=1.8,
                          centers=centers, shuffle=False, random_state=42)

        y[:n_samples // 2] = 0
        y[n_samples // 2:] = 1
```

```
In [41]: X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)
         log_reg = linear_model.LogisticRegression()
```

2.1 3.1 Binary Classification

```
In [42]: log_reg.fit(X_train, y_train)
```

```
Out[42]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                   penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                   verbose=0, warm_start=False)
```

```
In [43]: test_pred = log_reg.predict(X_test)
```

```
In [44]: (sum(test_pred == 1) + sum(test_pred == 0)) == len(test_pred)
```

```
Out[44]: True
```

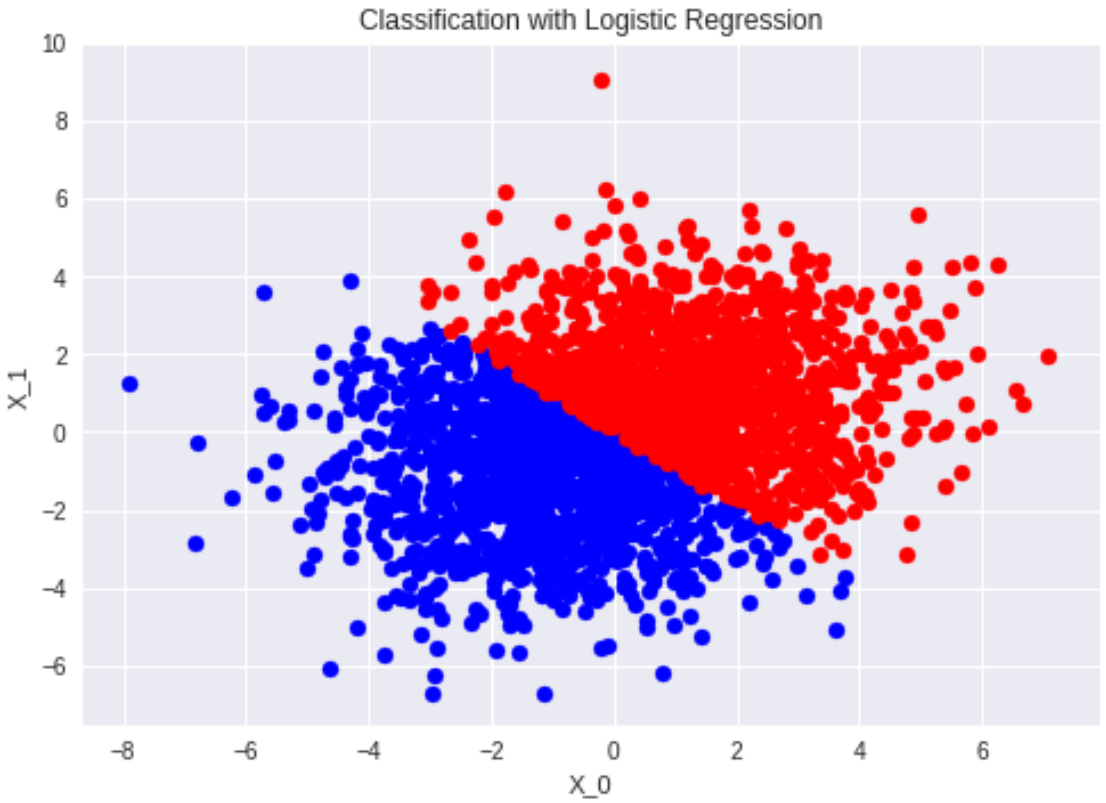
2.1.1 Q: Does the predictions of X_test contain values other than 0 or 1?

No.

2.1.2 Add scripts to logistic_clf.py to plot the data points in X_test using the function scatter() with different colors for different predicted classes.

```
In [45]: colors = 'br'
         for i, color in zip(log_reg.classes_, colors):
             idx = np.where(test_pred == i)
             plt.scatter(X_test[idx, 0], X_test[idx, 1], c=color, cmap=plt.cm.Paired)
```

```
In [46]: plt.title('Classification with Logistic Regression')
         plt.xlabel('X_0')
         plt.ylabel('X_1')
         plt.show()
```



2.1.3 Scatter plot of the true labels

```
In [47]: colors = 'br'
         for i, color in zip(log_reg.classes_, colors):
             idx = np.where(y_test == i)
             plt.scatter(X_test[idx, 0], X_test[idx, 1], c=color, cmap=plt.cm.Paired)

In [48]: plt.title('True Classes of Data')
         plt.xlabel('X_0')
         plt.ylabel('X_1')
         plt.show()
```

2.2 3.2 Classification Statistics

2.2.1 Q: How many wrong predictions does the LogisticRegression estimator make on the test data?

```
In [49]: print('Number of wrong predictions is: ', sum(y_test != test_pred))

Number of wrong predictions is:  567
```

Number of wrong predictions can also be calculated by the score.

```
In [50]: print('Score: ', log_reg.score(X_test, y_test))

Score:  0.7732
```

```
In [51]: print('Number of wrong predictions is: ', (1-0.7072) * len(X_test))

Number of wrong predictions is:  731.9999999999999
```