hw5_regression_matplotlib_fall2018

September 28, 2018

1 Data-X Spring 2018: Homework 05

1.0.1 Linear regression, logistic regression, matplotlib.

In this homework, you will do some exercises with prediction and plotting.

REMEMBER TO DISLPAY ALL OUTPUTS. If the question asks you to do something, make sure to print your results so we can easily see that you have done it.

1.1 Part 1 - Regression

1.1.1 Data:

Data Source: Data file is uploaded to bCourses and is named: **Energy.csv**

The dataset was created by Angeliki Xifara (Civil/Structural Engineer) and was processed by Athanasios Tsanas, Oxford Centre for Industrial and Applied Mathematics, University of Oxford, UK).

Data Description:

The dataset contains eight attributes of a building (or features, denoted by X1...X8) and response being the heating load on the building, y1.

- X1 Relative Compactness
- X2 Surface Area
- X3 Wall Area
- X4 Roof Area
- X5 Overall Height
- X6 Orientation
- X7 Glazing Area
- X8 Glazing Area Distribution
- y1 Heating Load

Q1.1 Read the data file in python. Check if there are any NaN values, and print the results. Describe data features in terms of type, distribution range (max and min), and mean values. Plot feature distributions. This step should give you clues about data sufficiency.

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
```

```
data = pd.read_csv("Energy.csv")
data.head()
```

Out[1]:

	X1	X2	X3	X4	X5	X6	X7	X8	Y1
0	0.98	514.5	294.0	110.25	7.0	2	0.0	0	15.55
1	0.98	514.5	294.0	110.25	7.0	3	0.0	0	15.55
2	0.98	514.5	294.0	110.25	7.0	4	0.0	0	15.55
3	0.98	514.5	294.0	110.25	7.0	5	0.0	0	15.55
4	0.90	563.5	318.5	122.50	7.0	2	0.0	0	20.84

In [2]:
```
print("X6 and X8 are integers but these integers each represent one class")
data.dtypes
```

```
X6 and X8 are integers but these integers each represent one class
```

Out[2]:
```
X1    float64
X2    float64
X3    float64
X4    float64
X5    float64
X6      int64
X7    float64
X8      int64
Y1    float64
dtype: object
```

In [3]:
```
print("nan in the dataframe: ", data.isnull().values.any())
```

```
nan in the dataframe:  False
```

In [4]:
```
data.describe()
```

Out[4]:

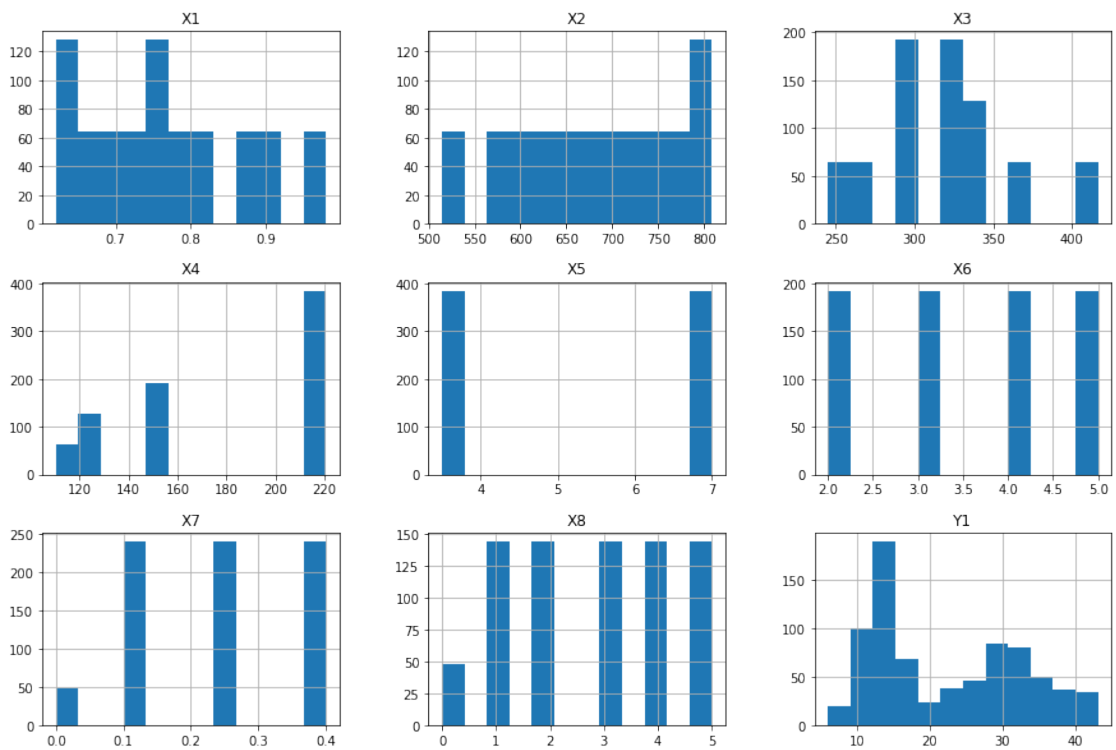
	X1	X2	X3	X4	X5	X6 \
count	768.000000	768.000000	768.000000	768.000000	768.00000	768.000000
mean	0.764167	671.708333	318.500000	176.604167	5.25000	3.500000
std	0.105777	88.086116	43.626481	45.165950	1.75114	1.118763
min	0.620000	514.500000	245.000000	110.250000	3.50000	2.000000
25%	0.682500	606.375000	294.000000	140.875000	3.50000	2.750000
50%	0.750000	673.750000	318.500000	183.750000	5.25000	3.500000
75%	0.830000	741.125000	343.000000	220.500000	7.00000	4.250000
max	0.980000	808.500000	416.500000	220.500000	7.00000	5.000000

	X7	X8	Y1
count	768.000000	768.00000	768.000000
mean	0.234375	2.81250	22.307201
std	0.133221	1.55096	10.090196
min	0.000000	0.00000	6.010000

```
25%      0.100000    1.75000   12.992500
50%      0.250000    3.00000   18.950000
75%      0.400000    4.00000   31.667500
max      0.400000    5.00000   43.100000
```

In [5]:
```
fig = plt.figure(figsize = (15,10))
ax = fig.gca()
data.hist(ax = ax, bins= 12)
None
```

```
c:\users\louis\documents\python_virtual_env\data-x\lib\site-packages\IPython\core\interactives
  exec(code_obj, self.user_global_ns, self.user_ns)
```



REGRESSION: LABELS ARE CONTINUOUS VALUES. Here the model is trained to predict a continuous value for each instance. On inputting a feature vector into the model, the trained model is able to predict a continuous value for that instance.

Q 1.2: Train a linear regression model on 80 percent of the given dataset, what is the intercept value and coefficient values.

In [6]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

train, test = train_test_split(data, test_size=0.2)
train_features, train_labels = train.drop(columns="Y1").values, train["Y1"].values
```

```
test_features, test_labels = test.drop(columns="Y1").values, test["Y1"].values

model = LinearRegression()
model.fit(train_features, train_labels)
print("slope coeficients: ", *model.coef_)
print("y intercept: ", model.intercept_)
```

```
slope coeficients:  -69.36383981350643 -0.07075170806241082 0.038663833208154724 -0.0547077706
y intercept:  94.79628826819793
```

Q.1.3: Report model performance using 'ROOT MEAN SQUARE' error metric on: 1. Data that was used for training(Training error)
2. On the 20 percent of unseen data (test error)

In [7]:
```
from sklearn.metrics import mean_squared_error
from math import sqrt

train_labels_predict = model.predict(train_features)
train_rmse = sqrt(mean_squared_error(train_labels, train_labels_predict))

test_labels_predict = model.predict(test_features)
test_rmse = sqrt(mean_squared_error(test_labels, test_labels_predict))

print("ROOT MEAN SQUARE ERROR for train set: ", model.score(train_features, train_label
print("ROOT MEAN SQUARE ERROR for test set: ", model.score(test_features, test_labels)
```

```
ROOT MEAN SQUARE ERROR for train set:  0.9150622770259813
ROOT MEAN SQUARE ERROR for test set:  0.9176724711463692
```

Q1.4: Lets us see the effect of amount of data on the performance of prediction model. Use varying amounts of Training data (100,200,300,400,500,all) to train regression models and report training error and validation error in each case. Validation data/Test data is the same as above for all these cases.

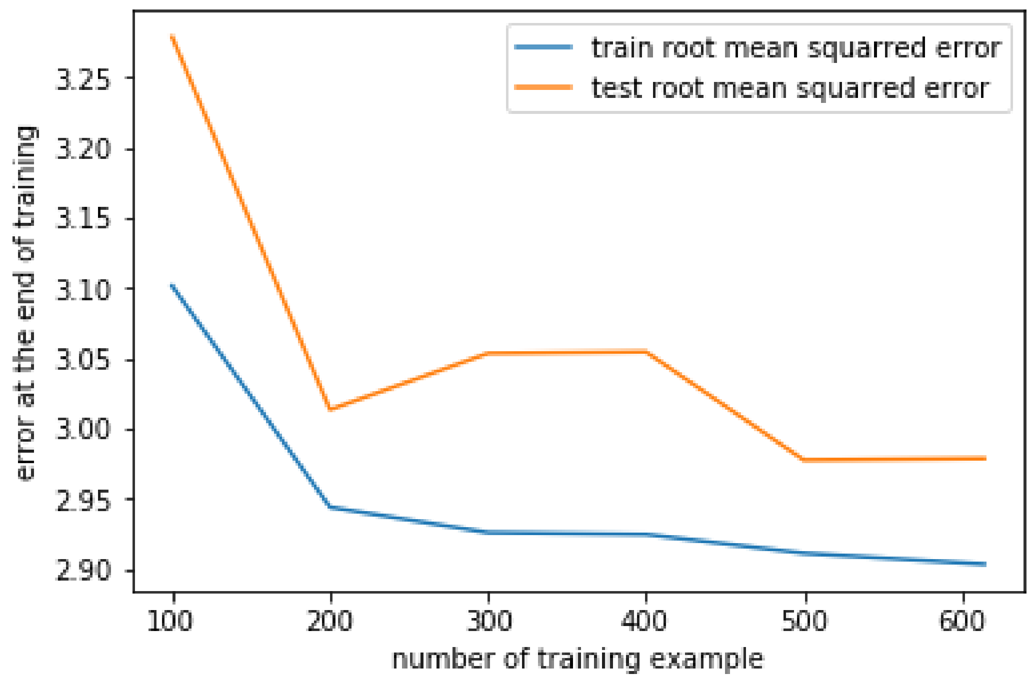
Plot error rates vs number of training examples. Both the training error and the validation error should be plotted. Comment on the relationship you observe in the plot, between the amount of data used to train the model and the validation accuracy of the model.

Hint: Use array indexing to choose varying data amounts

In [8]:
```
indices = np.arange(0, len(train_features))
np.random.shuffle(indices)

train_errors = []
test_errors = []
list_n_data = [100, 200, 300, 400, 500, len(train_features)]
for n_data in list_n_data:
    x = train_features[indices[0:n_data]]
```

```
        y = train_labels[indices[0:n_data]]
        x_all = train_features
        y_all = train_labels
        x_test = test_features
        y_test = test_labels

        model = LinearRegression()
        model.fit(x, y)

        # The error is always computed against the whole data set
        y_train_predict = model.predict(x_all)
        y_test_predict = model.predict(x_test)
        train_errors.append(sqrt(mean_squared_error(y_all, y_train_predict)))
        test_errors.append(sqrt(mean_squared_error(y_test, y_test_predict)))

    plt.plot(list_n_data, train_errors, label="train root mean squarred error")
    plt.plot(list_n_data, test_errors, label="test root mean squarred error")
    plt.xlabel("number of training example")
    plt.ylabel("error at the end of training")
    plt.legend()
```

```
Out[8]: <matplotlib.legend.Legend at 0x1f681257470>
```



We can see that the number of training example reduces the total mean squarred error for both the training set and the testing set. We can also see that the root mean squarred error is lower for the training data set, which is normal since it is the data set we are trying to fit.

1.2 Part 2 - Classification

CLASSIFICATION: LABELS ARE DISCRETE VALUES. Here the model is trained to classify each instance into a set of predefined discrete classes. On inputting a feature vector into the model, the trained model is able to predict a class of that instance. You can also output the probabilities of an instance belnging to a class.

__ Q 2.1: Bucket values of 'y1' i.e 'Heating Load' from the original dataset into 3 classes:__

0: 'Low' (< 14),
1: 'Medium' (14-28),
2: 'High' (>28)

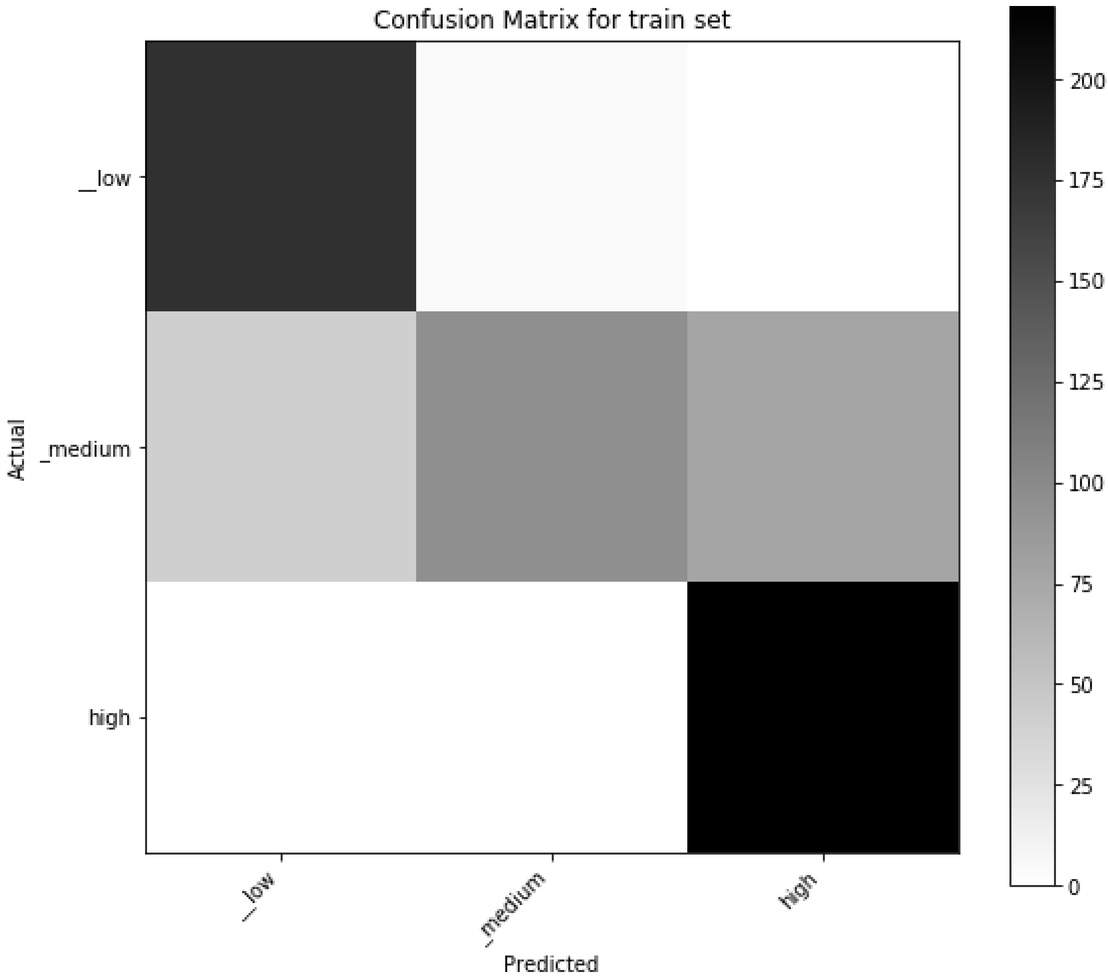
This converts the given dataset into a classification problem, classes being, Heating load is: *low, medium or high*. Use this datset with transformed 'heating load' for creating a logistic regression classifiction model that predicts heating load type of a building. Use test-train split ratio of 0.8 : 0.2.

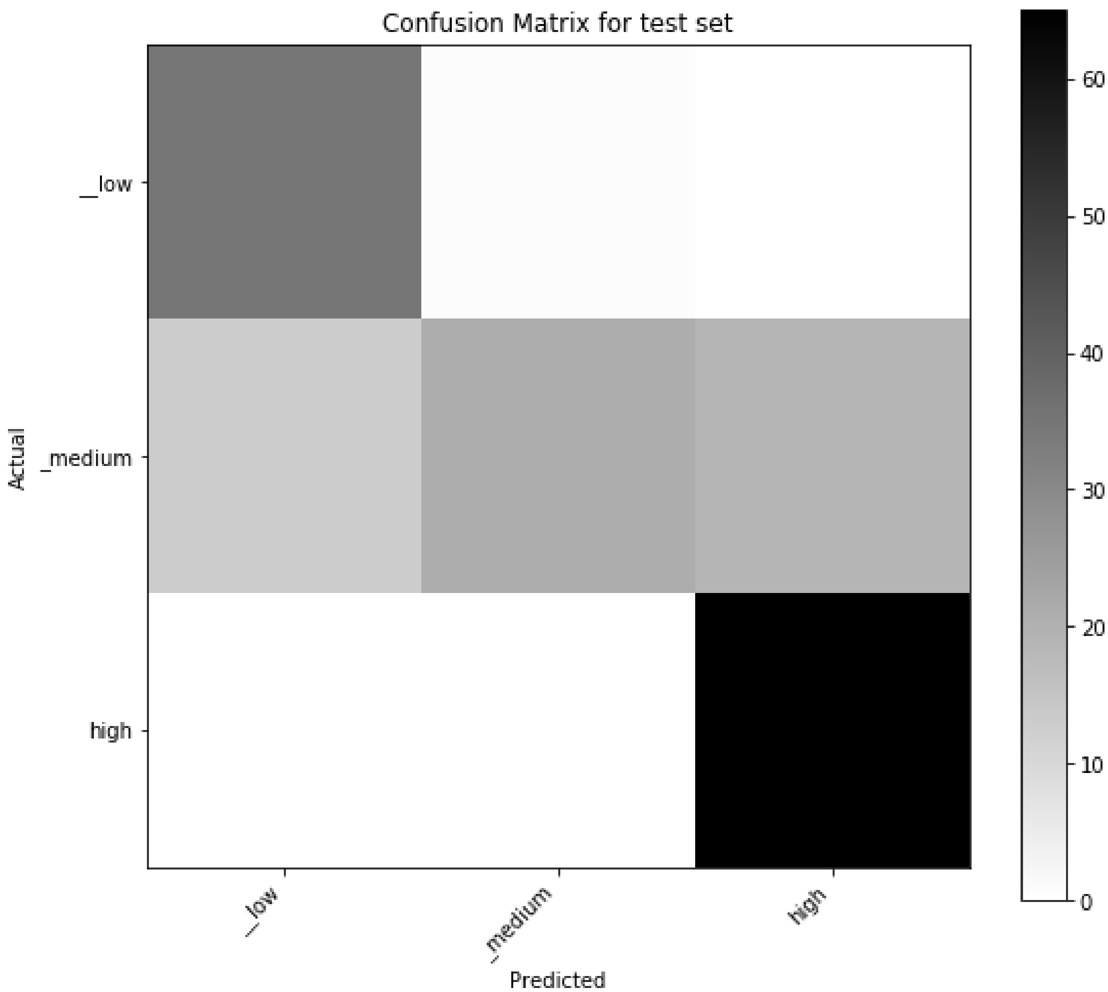
Report training and test accuracies and confusion matrices.

HINT: Use pandas.cut

In [9]:
```
from sklearn.linear_model import LogisticRegression
from pandas_ml import ConfusionMatrix

# Transform continuous data into categorical data
train_cut = pd.cut(train_labels, bins=[min(data['Y1'])-1, 14, 28, max(data['Y1'])], lal
test_cut = pd.cut(test_labels, bins=[min(data['Y1'])-1, 14, 28, max(data['Y1'])], label
new_train_labels = train_cut.codes
new_test_labels = test_cut.codes

# Train a logistic regression model to fit the data
model = LogisticRegression()
model.fit(train_features, new_train_labels)

new_y_train_predict = model.predict(train_features)
new_y_test_predict = model.predict(test_features)

train_accuracy = model.score(train_features, new_train_labels)
test_accuracy = model.score(test_features, new_test_labels)
train_confusion_matrix = ConfusionMatrix(new_train_labels, new_y_train_predict, labels=
test_confusion_matrix = ConfusionMatrix(new_test_labels, new_y_test_predict, labels=["

# PLOT
print("train accuracy: {}%".format(round(100*train_accuracy, 1)))
print("test accuracy: {}%".format(round(100*test_accuracy, 1)))

train_confusion_matrix.plot()
plt.title("Confusion Matrix for train set")

test_confusion_matrix.plot()
plt.title("Confusion Matrix for test set")

plt.show()
```

```
train accuracy: 80.0%
test accuracy: 78.6%
```





__ Q2.2: One of the preprocessing steps in Data science is Feature Scaling i.e getting all our data on the same scale by setting same Min-Max of feature values. This makes training less sensitive to the scale of features . Scaling is important in algorithms that use distance based classification, SVM or K means or those that involve gradient descent optimization. If we Scale features in the range [0,1] it is called unity based normalization.__

Perform unity based normalization on the above dataset and train the model again, compare model performance in training and validation with your previous model.

refer:http://scikit-learn.org/stable/modules/preprocessing.html#preprocessing-scaler more at: https://en.wikipedia.org/wiki/Feature_scaling

In [10]:
```
from sklearn.preprocessing import MinMaxScaler

minmaxscaler = MinMaxScaler()
minmaxscaler.fit(train_features)  # we do not want to consider testing set in the sca

scaled_features_train = minmaxscaler.transform(train_features)
scaled_features_test = minmaxscaler.transform(test_features)
```

```
model = LogisticRegression()
model.fit(scaled_features_train, new_train_labels)

scaled_train_y_predict = model.predict(scaled_features_train)
scaled_test_y_predict = model.predict(scaled_features_test)

scaled_train_accuracy = model.score(scaled_features_train, new_train_labels)
scaled_test_accuracy = model.score(scaled_features_test, new_test_labels)

print("train accuracy: {}%".format(round(100*scaled_train_accuracy, 1)))
print("test accuracy: {}%".format(round(100*scaled_test_accuracy, 1)))
```

```
train accuracy: 81.4%
test accuracy: 81.2%
```

We see a small increase in accuracy with the scaled dataset. However there is a good part of randomness, changing the training set and the test set can lead to examples where the accuracy in the scaled case is lower than in the non-scaled case. Therefore even though it is indeed useful to scale the features, it is hard to see it with a dataset of this size.

1.3 Part 3 - Matplotlib

Q 3.1a. Create a dataframe called `icecream` that has column `Flavor` with entries `Strawberry`, `Vanilla`, and `Chocolate` and another column with `Price` with entries `3.50`, `3.00`, and `4.25`.

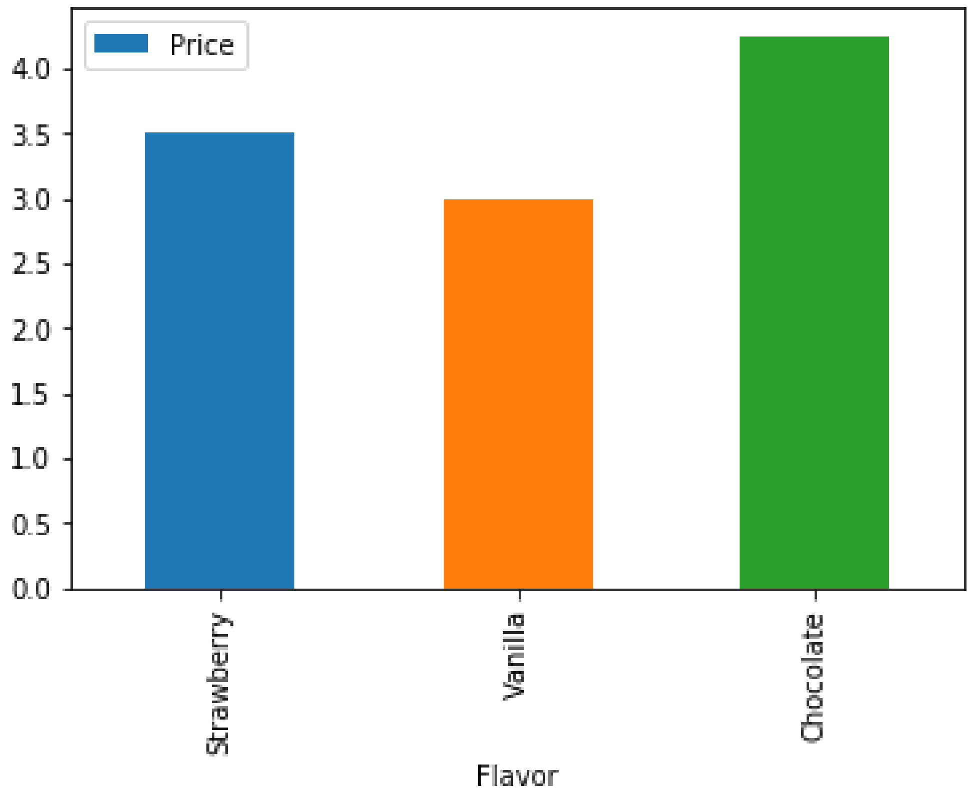
```
In [11]: df = pd.DataFrame()
         df.name = "icecream"
         df["Flavor"] = ["Strawberry", "Vanilla", "Chocolate"]
         df["Price"] = [3.5, 3, 4.25]
         df
```

Out[11]:

	Flavor	Price
0	Strawberry	3.50
1	Vanilla	3.00
2	Chocolate	4.25

Q 3.1b Create a bar chart representing the three flavors and their associated prices.

```
In [12]: df.plot(x="Flavor", y="Price", kind="bar")
         None
```



Q 3.2 Create 9 random plots (Hint: There is a numpy function for generating random data). The top three should be scatter plots (one with green dots, one with purple crosses, and one with blue triangles. The middle three graphs should be a line graph, a horizontal bar chart, and a histogram. The bottom three graphs should be trignometric functions (one sin, one cosine, one tangent).

```
In [13]: data = np.random.random(size=(9, 2, 500))

         plt.figure(figsize=(15, 10))

         plt.subplot(331)
         plt.plot(data[0, 0], data[0, 1], "g.")

         plt.subplot(332)
         plt.plot(data[1, 0], data[1, 1], c="#551a8b", marker="+", linestyle="")

         plt.subplot(333)
         plt.plot(data[2, 0], data[2, 1], "b>")

         plt.subplot(334)
         plt.plot(data[3, 0], data[3, 0] * data[3, 1, 0] + data[3, 1, 1])
```

```
plt.subplot(335)
plt.barh(["l1", "l2", "l3"], data[4, 0, 0:3])

plt.subplot(336)
plt.hist(data[5, 0])

plt.subplot(337)
plt.plot((np.sort(data[6, 0]) - 0.5)*np.pi, np.sin(np.sort(data[6, 0]*2*np.pi - np.pi

plt.subplot(338)
plt.plot((np.sort(data[7, 0]) - 0.5)*np.pi, np.cos(np.sort(data[7, 0]*2*np.pi - np.pi

plt.subplot(339)
plt.plot((np.sort(data[8, 0]) - 0.5)*np.pi/2, np.tan((np.sort(data[8, 0]) - 0.5)*(np.
```

```
Out[13]: [<matplotlib.lines.Line2D at 0x1f6839a1ba8>]
```