DS_Hw06

November 5, 2019

[28]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import sklearn
```

0.1 Because the previous dataset that I'm using,didn't contain much information thats suits for linear regression(Predicting a continuous value)).

0.2 Today I'm using another dataset that is about the personal medical cost.

[208]:

```
data=pd.read_csv('./insurance.csv')
print(data.info())
print('-----------------------------------------------------------------')
print(data.head())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
age         1338 non-null int64
sex         1338 non-null object
bmi         1338 non-null float64
children    1338 non-null int64
smoker      1338 non-null object
region      1338 non-null object
charges     1338 non-null float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
None
-----------------------------------------------------------------
   age     sex     bmi  children smoker     region      charges
0   19  female  27.900         0    yes  southwest  16884.92400
1   18    male  33.770         1     no  southeast   1725.55230
2   28    male  33.000         3     no  southeast   4449.46200
```

```
3   33    male  22.705          0      no  northwest  21984.47061
4   32    male  28.880          0      no  northwest   3866.85520
```

0.3 Firstly, we can find out there is no null value in the data set.

- age : Indicates the age of the person. It contains data of type ”int64”.
- sex : It refers to the gender of the person. It contains ”object” type data.
- bmi : It refers to the Body Mass Index of the person and contains the data of type ”float64”. BMI is a measure of the weight of a person, divided by the square of its length. Determines the person’s obesity value. The formula for USA and METRIC units is as follows:
- children : It refers to the number of children that a person has. It contains data of type ”int64”.
- smoker : Indicates whether the person smokes or not. It contains ”object” type data.
- region : Specifies which region the person is from. It contains ”object” type data.
- charges : The person’s total insurance premium is specified. Although not specified, it is assumed to be in US dollars. It contains ”float64” type data.

[160]:
```
data.describe()
```

[160]:

	age	bmi	children	charges
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.663397	1.094918	13270.422265
std	14.049960	6.098187	1.205493	12110.011237
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.296250	0.000000	4740.287150
50%	39.000000	30.400000	1.000000	9382.033000
75%	51.000000	34.693750	2.000000	16639.912515
max	64.000000	53.130000	5.000000	63770.428010

[86]:
```
data.corr()
```

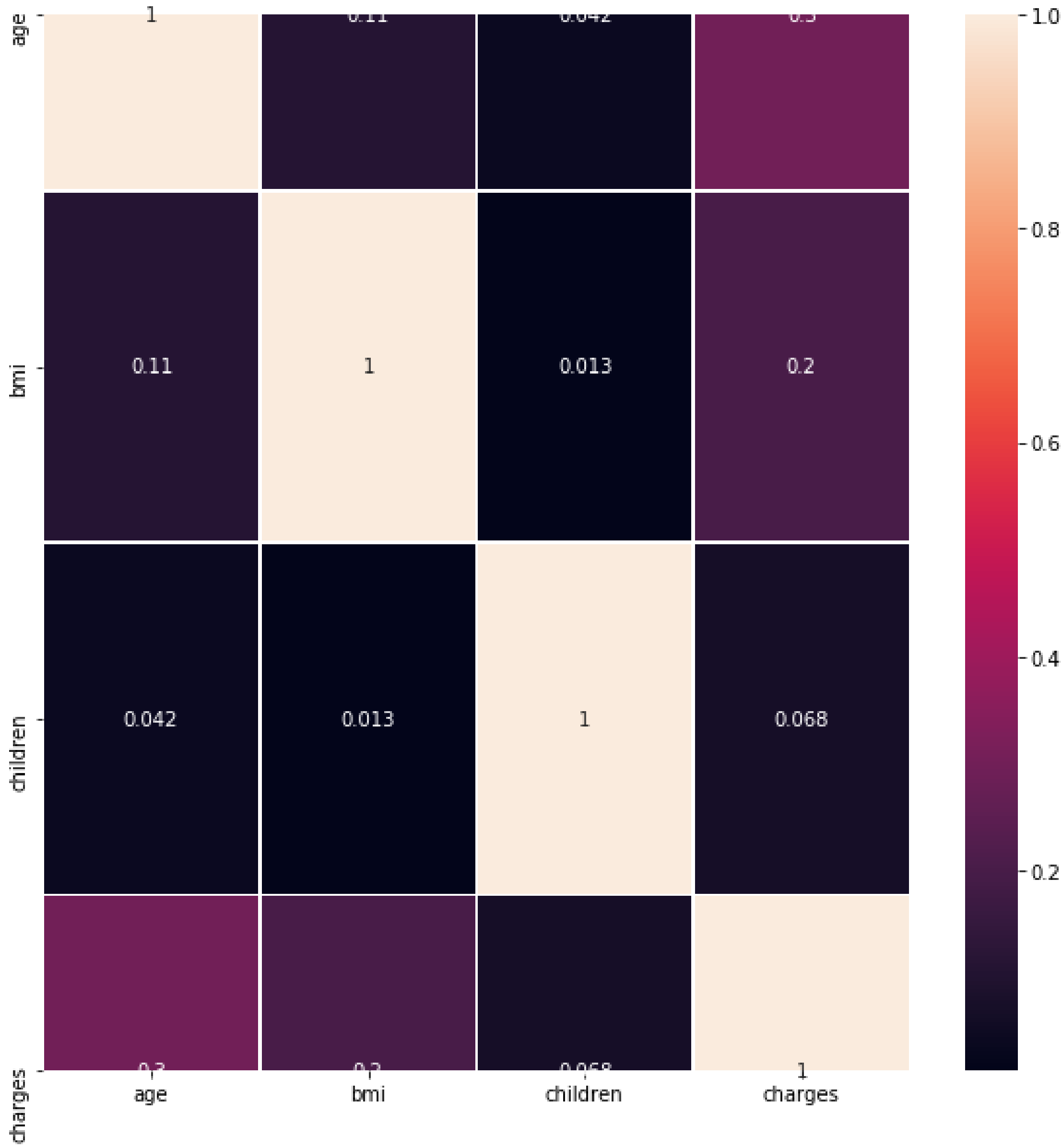
[86]:

	age	sex	bmi	children	smoker	charges
age	1.000000	-0.020856	0.109272	0.042469	-0.025019	0.299008
sex	-0.020856	1.000000	0.046371	0.017163	0.076185	0.057292
bmi	0.109272	0.046371	1.000000	0.012759	0.003750	0.198341
children	0.042469	0.017163	0.012759	1.000000	0.007673	0.067998
smoker	-0.025019	0.076185	0.003750	0.007673	1.000000	0.787251
charges	0.299008	0.057292	0.198341	0.067998	0.787251	1.000000

1 Basic understanding about dataset

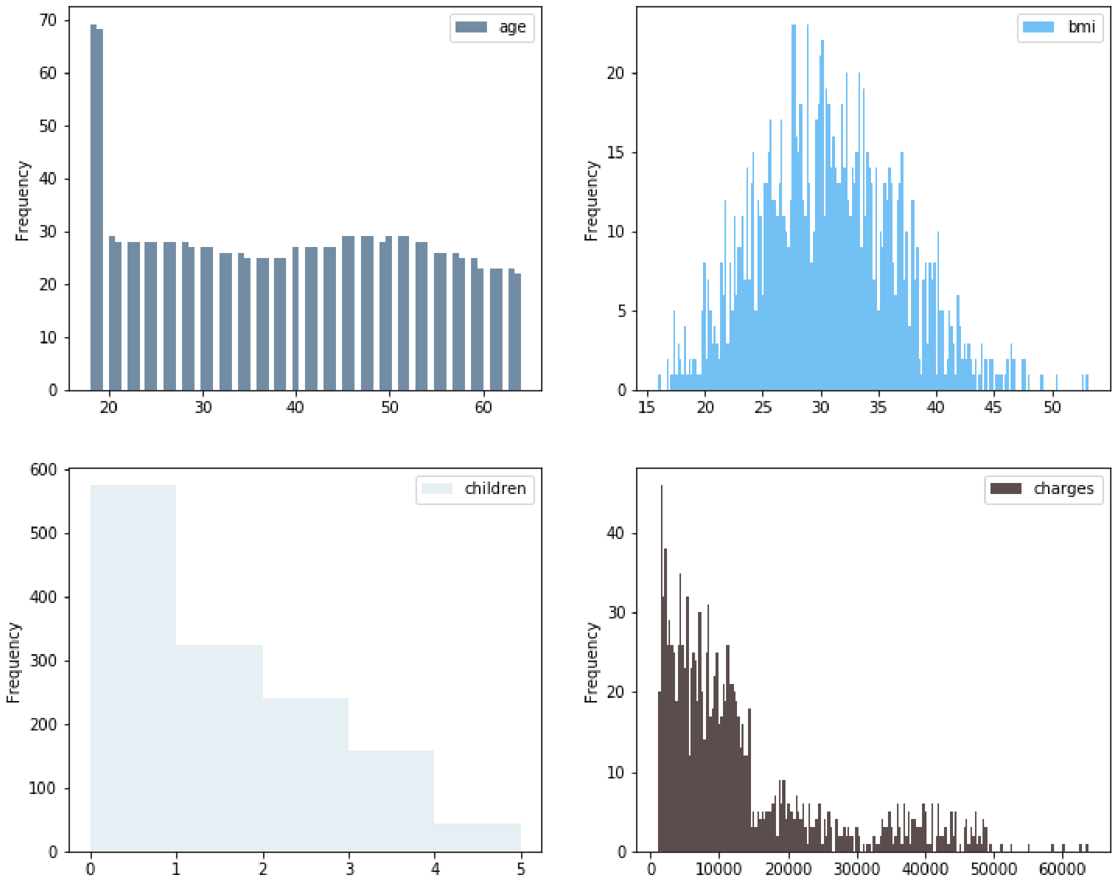
[77]:
```
fig, axes = plt.subplots(figsize=(10, 10))  # This method creates a figure and␣
 ↪a set of subplots
sns.heatmap(data=data.corr(), annot=True, linewidths=.5, ax=axes)  # Figure out␣
 ↪heatmap
```

```
# Parameters:
# data : 2D data for the heatmap.
# annot : If True, write the data value in each cell.
# linewidths : Width of the lines that will divide each cell.
# ax : Axes in which to draw the plot, otherwise use the currently-active Axes.
plt.show()  # Shows only plot and remove other informations
```



1.1 Data visualition

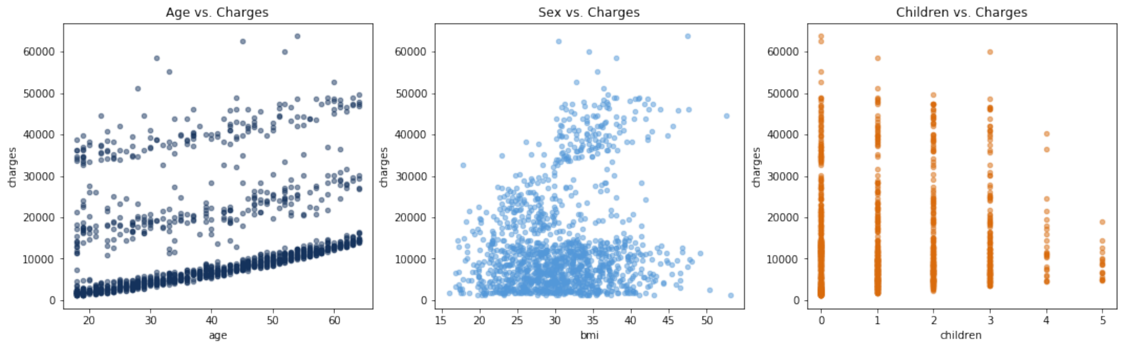
[78]:
```
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12, 10))
data.plot(kind="hist", y="age", bins=70, color="#728CA3", ax=axes[0][0])
data.plot(kind="hist", y="bmi", bins=200, color="#73C0F4", ax=axes[0][1])
data.plot(kind="hist", y="children", bins=5, color="#E6EFF3", ax=axes[1][0])
data.plot(kind="hist", y="charges", bins=200, color="#5A4D4C", ax=axes[1][1])
plt.show()
```



1.1.1 By the charts above we can know the distribution of each feature.

[191]:
```
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 5))
data.plot(kind='scatter', x='age', y='charges', alpha=0.5, color='#14325C',␣
 ↪ax=axes[0], title="Age vs. Charges")
data.plot(kind='scatter', x='bmi', y='charges', alpha=0.5, color='#5398D9',␣
 ↪ax=axes[1], title="Sex vs. Charges")
data.plot(kind='scatter', x='children', y='charges', alpha=0.5,␣
 ↪color='#D96B0C', ax=axes[2], title="Children vs. Charges")
```

```
plt.show()
```

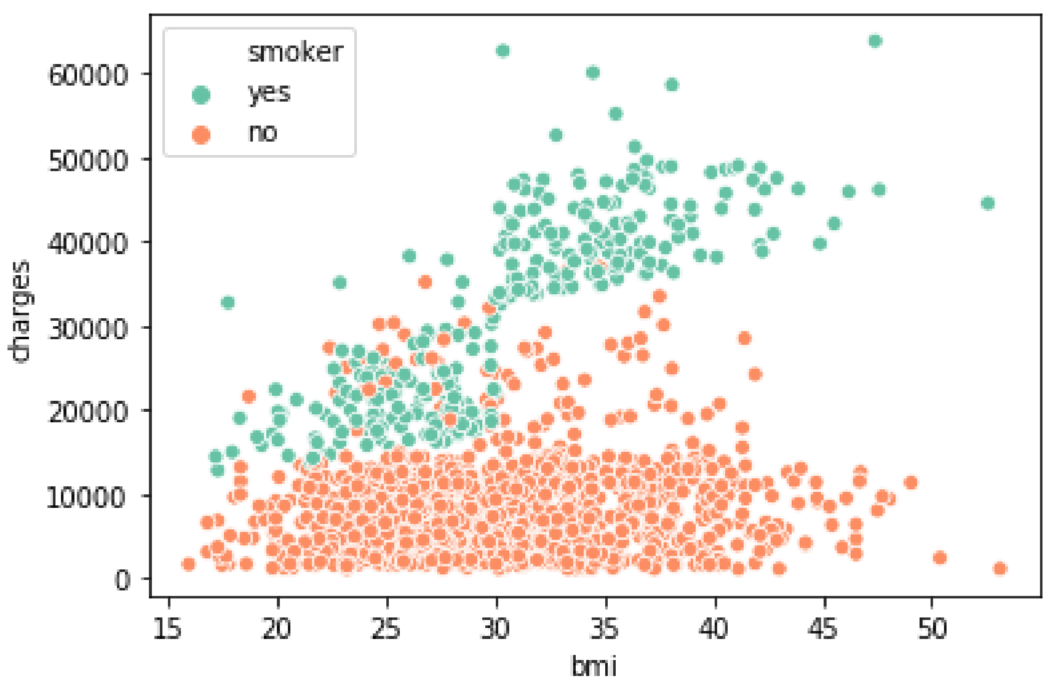


1.1.2 As far as age is concerned, we can find out the medical charges are positive proportional to the age, which is uqite make sense.

1.1.3 As for BMI, we do can find out those who have high BMI, is more likely to pay higher medical charges.

[192]:
```
sns.scatterplot(x="bmi", y="charges", data=data, palette='Set2', hue='smoker')
```

[192]: <matplotlib.axes._subplots.AxesSubplot at 0x7f203ddf0b70>



1.2 ### We can easily found out that under the same BMI the mediacal charges of smoker is significantly higher than the non-smokers.

1.2.1 And we convert the smoker and sex to numeric value.

[209]:
```
data.smoker=data.smoker.map({'yes':1,'no':0})
data.smoker.value_counts()
```

[209]:
```
0    1064
1     274
Name: smoker, dtype: int64
```

[210]:
```
data.sex=data.sex.map({'male':1,'female':0})
data.sex.value_counts()
```

[210]:
```
1    676
0    662
Name: sex, dtype: int64
```

1.3 Split the dataset to X and Y

[211]:
```
data.drop(['region'],axis=1,inplace=True)

X=data.drop(['charges'],axis=1)
Y=data['charges']

print(X.head())
```

```
   age  sex     bmi  children  smoker
0   19    0  27.900         0       1
1   18    1  33.770         1       0
2   28    1  33.000         3       0
3   33    1  22.705         0       0
4   32    1  28.880         0       0
```

[212]:
```
X["bmi"] = (X.bmi - np.min(X.bmi))/(np.max(X.bmi) - np.min(X.bmi))
print(X.head())
```

```
   age  sex       bmi  children  smoker
0   19    0  0.321227         0       1
1   18    1  0.479150         1       0
2   28    1  0.458434         3       0
```

```
3   33    1  0.181464         0        0
4   32    1  0.347592         0        0
```

[213]:
```
from sklearn.model_selection import train_test_split  # Import␣
↪"train_test_split" method
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures

x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2,␣
↪random_state=38)
print(x_train)
print(y_train)
```

```
      age  sex       bmi  children  smoker
623    18    1  0.472828         0       1
581    19    1  0.393597         0       0
200    19    0  0.434490         0       0
1274   26    1  0.298628         0       1
111    55    0  0.369653         2       0
…    …   …       …       …     …
737    26    1  0.208232         2       0
1282   18    0  0.153349         0       1
900    49    1  0.176352         0       0
316    50    1  0.437046         0       0
53     36    1  0.496906         0       1

[1070 rows x 5 columns]
623     34617.84065
581      1639.56310
200      2130.67590
1274    17043.34140
111     11881.35800
           …
737      3484.33100
1282    14283.45940
900      8688.85885
316      8835.26495
53      37742.57570
Name: charges, Length: 1070, dtype: float64
```

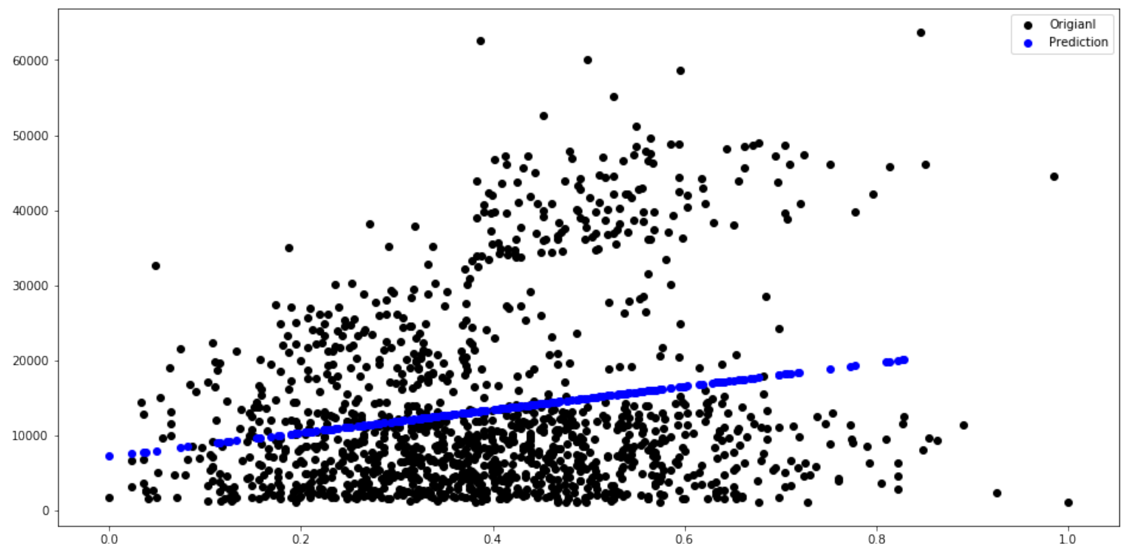
1.4 Simple linear regression :

1.4.1 we choose BMI as x,to predict the corresponding charges.

[214]:
```
simple_linear_reg=LinearRegression()
simple_linear_reg.fit(x_train.bmi.values.reshape(-1,1),y_train)
Prediction=simple_linear_reg.predict(x_test.bmi.values.reshape(-1,1))

plt.figure(figsize=(16,8))

plt.scatter(X.bmi,Y,c='black',label='Origianl')
plt.scatter(x_test.bmi,Prediction,c='blue',label='Prediction')
plt.legend()
plt.show()
```



1.5 ### We can easily see that because the data is too complicated, the results predicted by simple linear regression is not very accurate.

1.5.1 So following I will use some regression model try to have a better result.

1.6 Multiple linear regression

[215]:
```
multiple_linear_reg = LinearRegression(fit_intercept=False,normalize=True)  #␣
↪Create a instance for Linear Regression model
multiple_linear_reg.fit(x_train, y_train)
```

[215]:
```
LinearRegression(copy_X=True, fit_intercept=False, n_jobs=None, normalize=True)
```

1.7 Polynomial linear regression

[216]:
```
polynomial_features = PolynomialFeatures(degree=3)  # Create a␣
↪PolynomialFeatures instance in degree 3
x_train_poly = polynomial_features.fit_transform(x_train)  # Fit and transform␣
↪the training data to polynomial
x_test_poly = polynomial_features.fit_transform(x_test)  # Fit and transform␣
↪the testing data to polynomial

polynomial_reg = LinearRegression(fit_intercept=False)  # Create a instance for␣
↪Linear Regression model
polynomial_reg.fit(x_train_poly, y_train)  # Fit data to the model
```

[216]:
```
LinearRegression(copy_X=True, fit_intercept=False, n_jobs=None, normalize=False)
```

1.8 Decision tree regression

[217]:
```
from sklearn.tree import DecisionTreeRegressor  # Import Decision Tree␣
↪Regression model

decision_tree_reg = DecisionTreeRegressor(max_depth=5, random_state=13)  #␣
↪Create a instance for Decision Tree Regression model
decision_tree_reg.fit(x_train, y_train)  # Fit data to the model
```

[217]:
```
DecisionTreeRegressor(criterion='mse', max_depth=5, max_features=None,
                      max_leaf_nodes=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      presort=False, random_state=13, splitter='best')
```

1.9 Random forest regrssion

[218]:
```
from sklearn.ensemble import RandomForestRegressor  # Import Random Forest␣
↪Regression model

random_forest_reg = RandomForestRegressor(n_estimators=400, max_depth=5,␣
↪random_state=13)  # Create a instance for Random Forest Regression model
random_forest_reg.fit(x_train, y_train)  # Fit data to the model
```

[218]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=5,
                      max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=400,
```

```
n_jobs=None, oob_score=False, random_state=13, verbose=0,
warm_start=False)
```

1.10 Evaluation Model : Because it's hard to visualize the result of each model. In this section we will do some measurements to evaluate the performance on the models we fit.

1.11 I will use following metric to determine the performance of each model

- R2 score
- RMSE score

[219]:
```
from sklearn.model_selection import cross_val_predict  # For K-Fold Cross␣
↪Validation
from sklearn.metrics import r2_score  # For find accuracy with R2 Score
from sklearn.metrics import mean_squared_error  # For MSE
from math import sqrt  # For squareroot operation
```

Evaluating Multiple Linear Regression Model

[221]:
```
# Prediction with training dataset:
y_pred_MLR_train = multiple_linear_reg.predict(x_train)
# Prediction with testing dataset:
y_pred_MLR_test = multiple_linear_reg.predict(x_test)

# Find training accuracy for this model:
accuracy_MLR_train = r2_score(y_train, y_pred_MLR_train)
print("Training Accuracy for Multiple Linear Regression Model: ",␣
↪accuracy_MLR_train)

# Find testing accuracy for this model:
accuracy_MLR_test = r2_score(y_test, y_pred_MLR_test)
print("Testing Accuracy for Multiple Linear Regression Model: ",␣
↪accuracy_MLR_test)

# Find RMSE for training data:
RMSE_MLR_train = sqrt(mean_squared_error(y_train, y_pred_MLR_train))
print("RMSE for Training Data: ", RMSE_MLR_train)

# Find RMSE for testing data:
RMSE_MLR_test = sqrt(mean_squared_error(y_test, y_pred_MLR_test))
print("RMSE for Testing Data: ", RMSE_MLR_test)

# Prediction with 10-Fold Cross Validation:
y_pred_cv_MLR = cross_val_predict(multiple_linear_reg, X, Y, cv=10)
```

```
# Find accuracy after 10-Fold Cross Validation
accuracy_cv_MLR = r2_score(Y, y_pred_cv_MLR)
print("Accuracy for 10-Fold Cross Predicted Multiple Linaer Regression Model:␣
↪", accuracy_cv_MLR)
```

```
Training Accuracy for Multiple Linear Regression Model:  0.7349353567311003
Testing Accuracy for Multiple Linear Regression Model:  0.6930564433613213
RMSE for Training Data:  6337.433153036048
RMSE for Testing Data:  6233.016718587124
Accuracy for 10-Fold Cross Predicted Multiple Linaer Regression Model:
0.725833988666255
```

Evaluating Polynomial Regression Model

[222]:
```
y_pred_PR_train = polynomial_reg.predict(x_train_poly)

# Prediction with testing dataset:
y_pred_PR_test = polynomial_reg.predict(x_test_poly)

# Find training accuracy for this model:
accuracy_PR_train = r2_score(y_train, y_pred_PR_train)
print("Training Accuracy for Polynomial Regression Model: ", accuracy_PR_train)

# Find testing accuracy for this model:
accuracy_PR_test = r2_score(y_test, y_pred_PR_test)
print("Testing Accuracy for Polynomial Regression Model: ", accuracy_PR_test)

# Find RMSE for training data:
RMSE_PR_train = sqrt(mean_squared_error(y_train, y_pred_PR_train))
print("RMSE for Training Data: ", RMSE_PR_train)

# Find RMSE for testing data:
RMSE_PR_test = sqrt(mean_squared_error(y_test, y_pred_PR_test))
print("RMSE for Testing Data: ", RMSE_PR_test)

# Prediction with 10-Fold Cross Validation:
y_pred_cv_PR = cross_val_predict(polynomial_reg, polynomial_features.
↪fit_transform(X), Y, cv=10)

# Find accuracy after 10-Fold Cross Validation
accuracy_cv_PR = r2_score(Y, y_pred_cv_PR)
print("Accuracy for 10-Fold Cross Predicted Polynomial Regression Model: ",␣
↪accuracy_cv_PR)
```

```
Training Accuracy for Polynomial Regression Model:  0.8541761284562099
Testing Accuracy for Polynomial Regression Model:  0.8159698674199801
RMSE for Training Data:  4700.583836612859
```

```
RMSE for Testing Data:  4826.290963282682
Accuracy for 10-Fold Cross Predicted Polynomial Regression Model:
0.8391072917717248
```

Evaluating Decision Tree Regression Mode

[223]:
```python
# Prediction with training dataset:
y_pred_DTR_train = decision_tree_reg.predict(x_train)

# Prediction with testing dataset:
y_pred_DTR_test = decision_tree_reg.predict(x_test)

# Find training accuracy for this model:
accuracy_DTR_train = r2_score(y_train, y_pred_DTR_train)
print("Training Accuracy for Decision Tree Regression Model: ",␣
↪accuracy_DTR_train)

# Find testing accuracy for this model:
accuracy_DTR_test = r2_score(y_test, y_pred_DTR_test)
print("Testing Accuracy for Decision Tree Regression Model: ",␣
↪accuracy_DTR_test)

# Find RMSE for training data:
RMSE_DTR_train = sqrt(mean_squared_error(y_train, y_pred_DTR_train))
print("RMSE for Training Data: ", RMSE_DTR_train)

# Find RMSE for testing data:
RMSE_DTR_test = sqrt(mean_squared_error(y_test, y_pred_DTR_test))
print("RMSE for Testing Data: ", RMSE_DTR_test)

# Prediction with 10-Fold Cross Validation:
y_pred_cv_DTR = cross_val_predict(decision_tree_reg, X, Y, cv=10)

# Find accuracy after 10-Fold Cross Validation
accuracy_cv_DTR = r2_score(Y, y_pred_cv_DTR)
print("Accuracy for 10-Fold Cross Predicted Decision Tree Regression Model: ",␣
↪accuracy_cv_DTR)
```

```
Training Accuracy for Decision Tree Regression Model:  0.8833393572717199
Testing Accuracy for Decision Tree Regression Model:  0.8163629639882319
RMSE for Training Data:  4204.357846314286
RMSE for Testing Data:  4821.133621392454
Accuracy for 10-Fold Cross Predicted Decision Tree Regression Model:
0.8494241031595924
```

Evaluate for random forest

[224]:
```python
# Prediction with training dataset:
y_pred_RFR_train = random_forest_reg.predict(x_train)
```

```
# Prediction with testing dataset:
y_pred_RFR_test = random_forest_reg.predict(x_test)

# Find training accuracy for this model:
accuracy_RFR_train = r2_score(y_train, y_pred_RFR_train)
print("Training Accuracy for Random Forest Regression Model: ",␣
↪accuracy_RFR_train)

# Find testing accuracy for this model:
accuracy_RFR_test = r2_score(y_test, y_pred_RFR_test)
print("Testing Accuracy for Random Forest Regression Model: ",␣
↪accuracy_RFR_test)

# Find RMSE for training data:
RMSE_RFR_train = sqrt(mean_squared_error(y_train, y_pred_RFR_train))
print("RMSE for Training Data: ", RMSE_RFR_train)

# Find RMSE for testing data:
RMSE_RFR_test = sqrt(mean_squared_error(y_test, y_pred_RFR_test))
print("RMSE for Testing Data: ", RMSE_RFR_test)

# Prediction with 10-Fold Cross Validation:
y_pred_cv_RFR = cross_val_predict(random_forest_reg, X, Y, cv=10)

# Find accuracy after 10-Fold Cross Validation
accuracy_cv_RFR = r2_score(Y, y_pred_cv_RFR)
print("Accuracy for 10-Fold Cross Predicted Random Forest Regression Model: ",␣
↪accuracy_cv_RFR)
```

```
Training Accuracy for Random Forest Regression Model:  0.8907930796950516
Testing Accuracy for Random Forest Regression Model:  0.853979607357261
RMSE for Training Data:  4067.8279000224125
RMSE for Testing Data:  4299.082577404704
Accuracy for 10-Fold Cross Predicted Random Forest Regression Model:
0.8573950228640141
```

[225]:
```
training_accuracies = [accuracy_MLR_train, accuracy_PR_train,␣
↪accuracy_DTR_train, accuracy_RFR_train]
testing_accuracies = [accuracy_MLR_test, accuracy_PR_test, accuracy_DTR_test,␣
↪accuracy_RFR_test]
training_RMSE = [RMSE_MLR_train, RMSE_PR_train, RMSE_DTR_train, RMSE_RFR_train]
testing_RMSE = [RMSE_MLR_test, RMSE_PR_test, RMSE_DTR_test, RMSE_RFR_test]
cv_accuracies = [accuracy_cv_MLR, accuracy_cv_PR, accuracy_cv_DTR,␣
↪accuracy_cv_RFR]
parameters = ["fit_intercept=False", "fit_intercept=False", "max_depth=5",␣
↪"n_estimators=400, max_depth=5"]
```

```
table_data = {"Parameters": parameters, "Training Accuracy":␣
↪training_accuracies, "Testing Accuracy": testing_accuracies,
              "Training RMSE": training_RMSE, "Testing RMSE": testing_RMSE,␣
↪"10-Fold Score": cv_accuracies}
model_names = ["Multiple Linear Regression", "Polynomial Regression", "Decision␣
↪Tree Regression", "Random Forest Regression"]

table_dataframe = pd.DataFrame(data=table_data, index=model_names)
table_dataframe
```

[225]:

```
                                              Parameters  Training Accuracy  \
Multiple Linear Regression            fit_intercept=False           0.734935
Polynomial Regression                 fit_intercept=False           0.854176
Decision Tree Regression                      max_depth=5           0.883339
Random Forest Regression    n_estimators=400, max_depth=5           0.890793

                            Testing Accuracy  Training RMSE  Testing RMSE  \
Multiple Linear Regression          0.693056    6337.433153   6233.016719
Polynomial Regression               0.815970    4700.583837   4826.290963
Decision Tree Regression            0.816363    4204.357846   4821.133621
Random Forest Regression            0.853980    4067.827900   4299.082577

                            10-Fold Score
Multiple Linear Regression       0.725834
Polynomial Regression            0.839107
Decision Tree Regression         0.849424
Random Forest Regression         0.857395
```

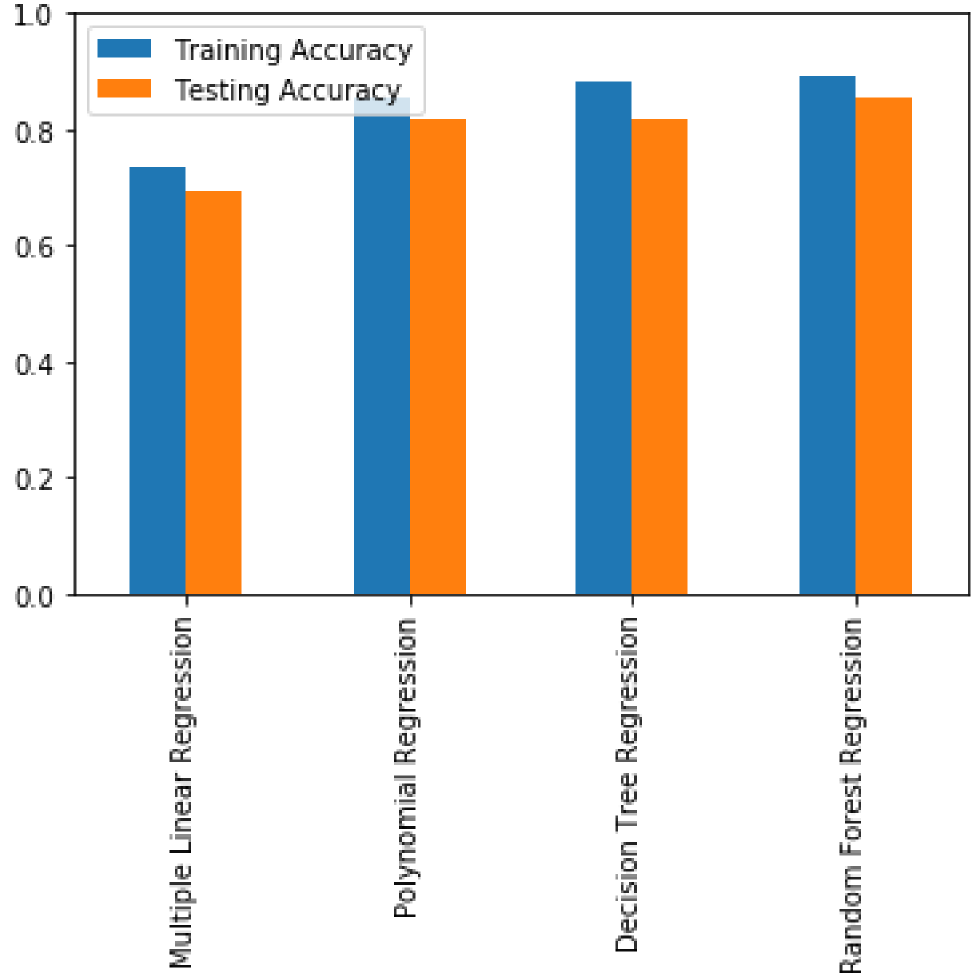
Now let's compare the training and testing accuracy of each model:

[226]:

```
table_dataframe.iloc[:, 1:3].plot(kind="bar", ylim=[0.0, 1.0])
```

[226]:

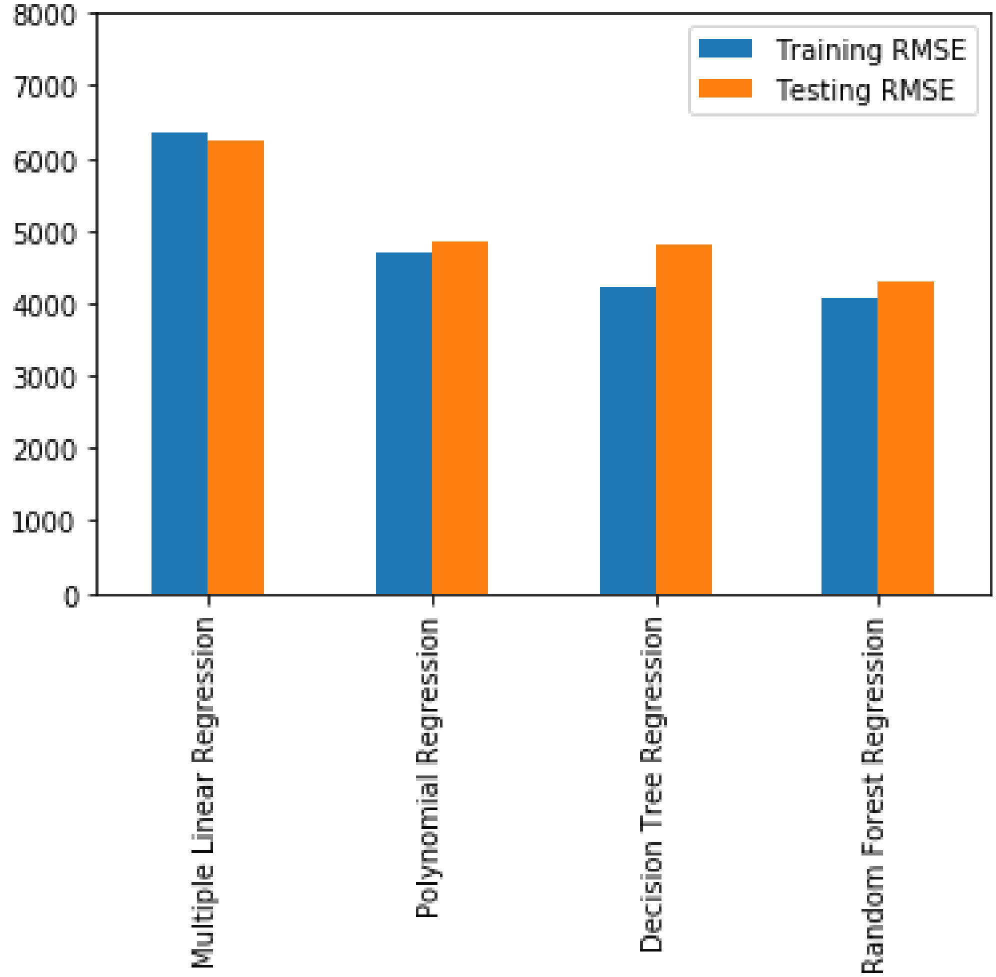
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f203c0b0ba8>
```



Let's compare each model's training and testing RMSE:

[228]:
```
table_dataframe.iloc[:, 3:5].plot(kind="bar", ylim=[0.0, 8000])
```

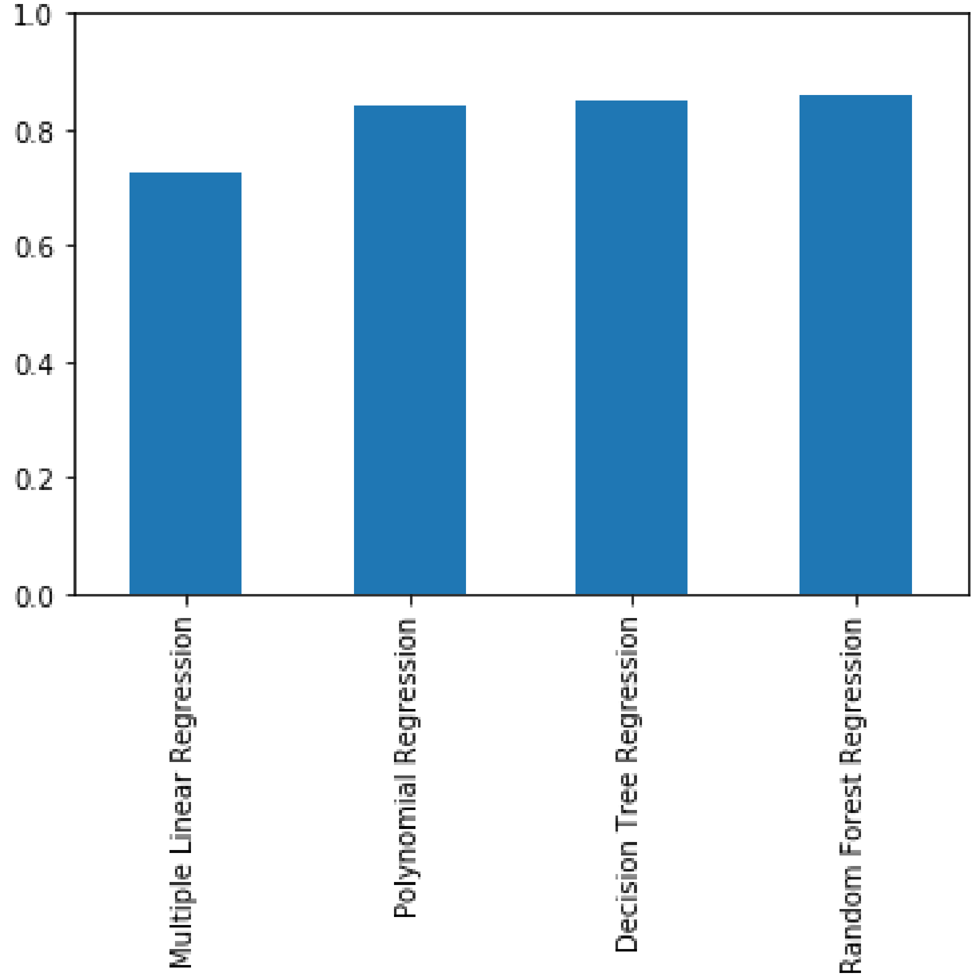
[228]: <matplotlib.axes._subplots.AxesSubplot at 0x7f203d010780>



Finally, compare the score values for 10-Fold Cross Validation:

[229]:
```
table_dataframe.iloc[:, 5].plot(kind="bar", ylim=[0.0, 1.0])
```

[229]: <matplotlib.axes._subplots.AxesSubplot at 0x7f203d265eb8>



As you can see, The result predicted by the multiple linear regreession is the least accurate, which is roughly 70% accuracy. As for polynomail , decision tree , random forest regression, all of them are approximately 80% ~ 85% accuracy.

And the random forest regression has the highest accuracy, which is roughly 85%.