9mmf34gg0

February 17, 2026

Task 04: Predicting Insurance Claim Amounts.

Objective: Estimate the medical insurance claim amount based on persnal data.

Dataset: Medical Cost Personal Dataset. About Dataset: Context: Machine Learning with R by Brett Lantz is a book that provides an introduction to machine learning using R. As far as I can tell, Packt Publishing does not make its datasets available online unless you buy the book and create a user account which can be a problem if you are checking the book out from the library or borrowing the book from a friend. All of these datasets are in the public domain but simply needed some cleaning up and recoding to match the format in the book. Content: Columns: age: Age of primary beneficiary. sex: Insurance contractor gender, female, male bmi: Body mass index, providing an understanding of body, weights that are relatively high or low relative to height, objective index of body weight (kg / m ^ 2) using the ratio of height to weight, ideally 18.5 to 24.9. children: Number of children covered by health insurance / Number of dependents. smoker: Smoking. region: The beneficiary's residential area in the US, northeast, southeast, southwest, northwest. charges: Individual medical costs billed by health.

Load The Dataset:

[1]:
```
import pandas as pd
```

[2]:
```
Dataset = pd.read_csv("insurance.csv")
```

Data Exploration:

[3]:
```
Dataset.head()
```

[3]:

	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

[4]:
```
Dataset.tail()
```

[4]:

	age	sex	bmi	children	smoker	region	charges
1333	50	male	30.97	3	no	northwest	10600.5483
1334	18	female	31.92	0	no	northeast	2205.9808
1335	18	female	36.85	0	no	southeast	1629.8335

```
1336   21  female  25.80         0     no  southwest    2007.9450
1337   61  female  29.07         0    yes  northwest   29141.3603
```

[5]:
```
Dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1338 non-null   int64
 1   sex       1338 non-null   object
 2   bmi       1338 non-null   float64
 3   children  1338 non-null   int64
 4   smoker    1338 non-null   object
 5   region    1338 non-null   object
 6   charges   1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

[6]:
```
Dataset.describe()
```

[6]:

	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

[7]:
```
Dataset.shape
```

[7]: (1338, 7)

[8]:
```
Dataset.columns
```

[8]:
```
Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges'],
dtype='object')
```

[9]:
```
Dataset.dtypes
```

[9]:
```
age           int64
sex          object
bmi         float64
children      int64
```

```
smoker        object
region        object
charges      float64
dtype: object
```

Instructions: Visualize how BMI, age and smoking status impact insurance charges.

[10]:
```
import matplotlib as pyplot
from matplotlib import pyplot as plt

import seaborn as sns
```

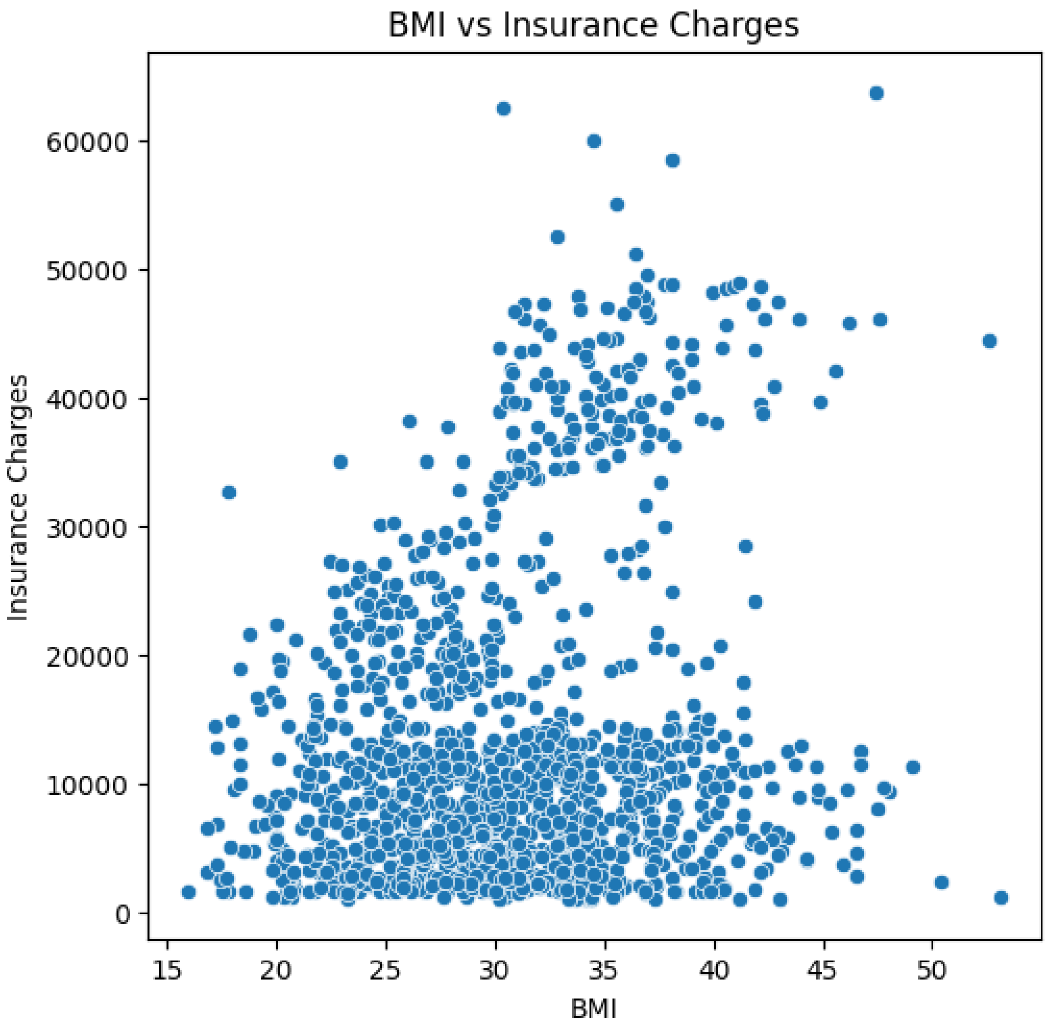
BMI vs Insurance Charges:

[11]:
```
plt.figure(figsize=(6,6))

sns.scatterplot(x=Dataset["bmi"], y=Dataset["charges"])

plt.title("BMI vs Insurance Charges")
plt.xlabel("BMI")
plt.ylabel("Insurance Charges")

plt.show()
```



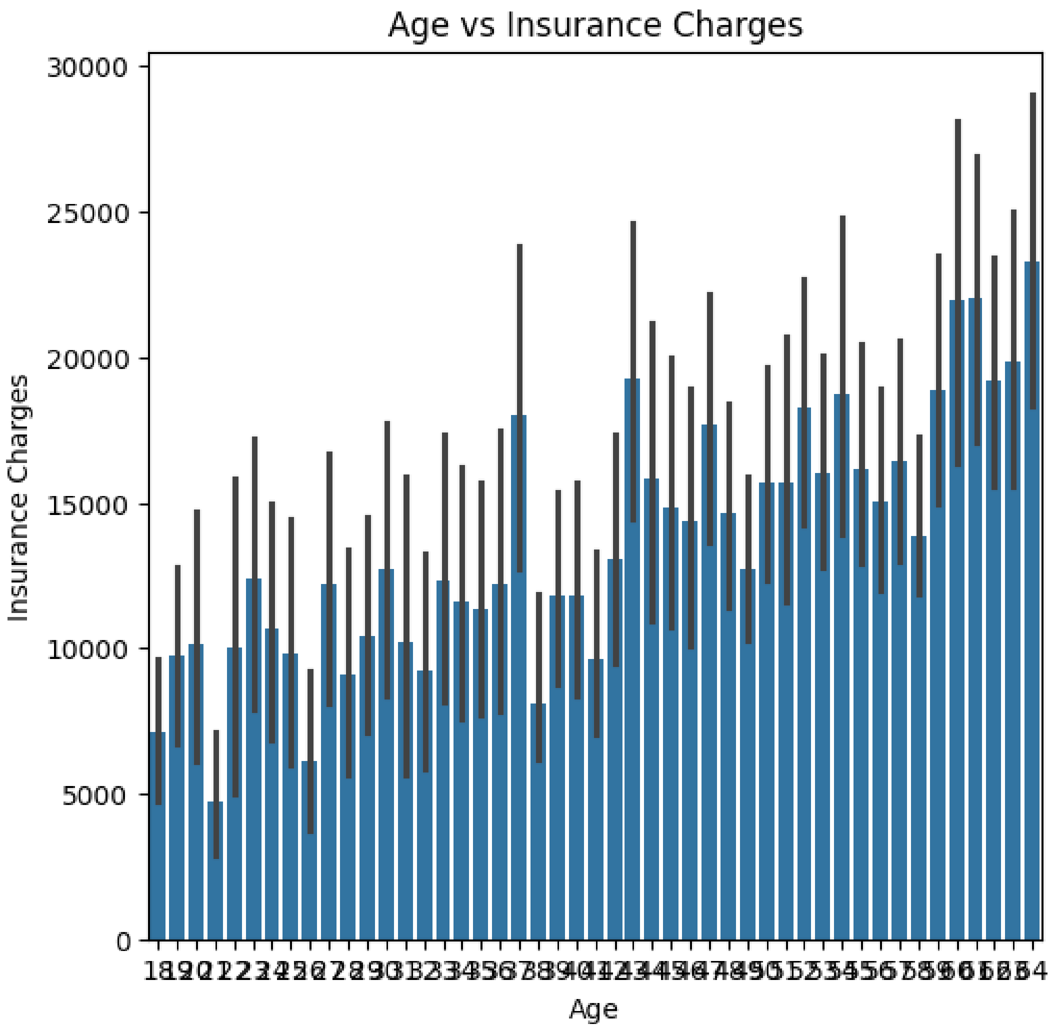
Age vs Insurance Charges:

[12]:
```
plt.figure(figsize=(6,6))

sns.barplot(x=Dataset["age"], y=Dataset["charges"])

plt.title("Age vs Insurance Charges")
plt.xlabel("Age")
plt.ylabel("Insurance Charges")

plt.show()
```



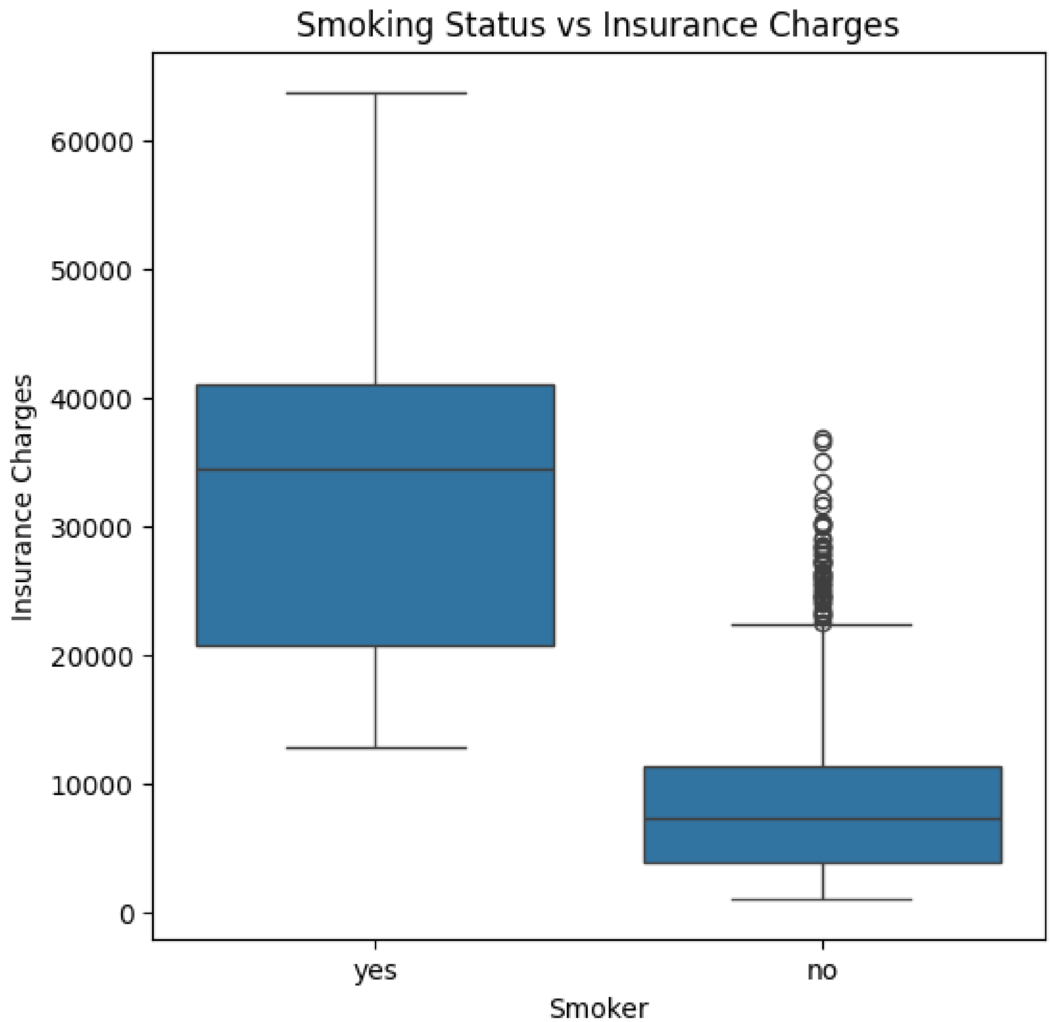
Smoking Status vs Insurance Charges:

[13]:
```
plt.figure(figsize=(6,6))

sns.boxplot(x=Dataset["smoker"], y=Dataset["charges"])

plt.title("Smoking Status vs Insurance Charges")
plt.xlabel("Smoker")
plt.ylabel("Insurance Charges")

plt.show()
```



PaitPlot For All The Combinations:

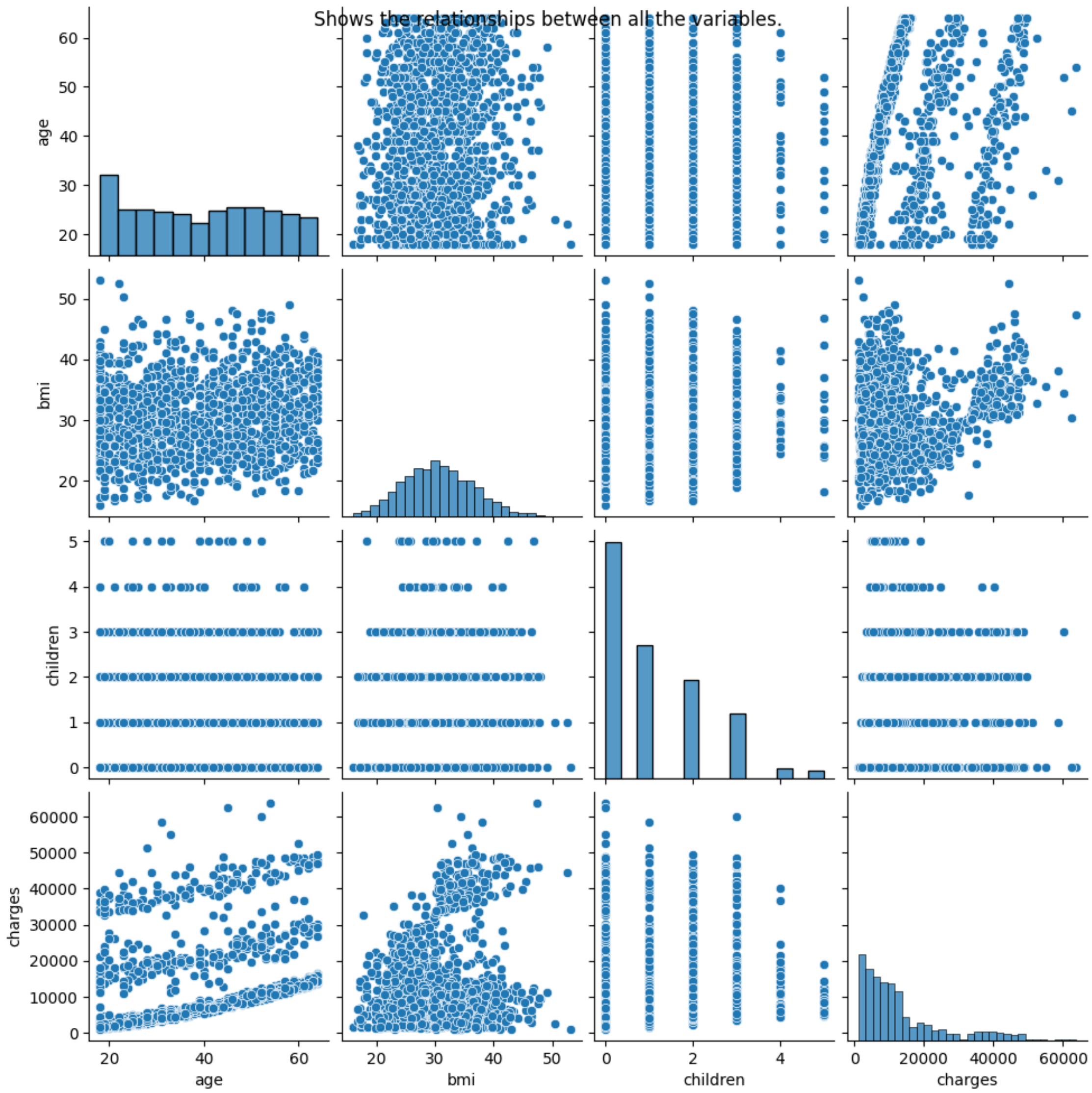
[14]:
```
plt.figure(figsize=(6,6))

sns.pairplot(Dataset)

plt.suptitle("Shows the relationships between all the variables.")

plt.show()
```

```
<Figure size 600x600 with 0 Axes>
```



Handle Missing values:

[15]:
```
Dataset.isnull().sum()
```

[15]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

[16]:
```
Dataset = pd.get_dummies(Dataset, drop_first=True)
```

[17]:
```
Dataset.head()
```

[17]:
```
   age     bmi  children      charges  sex_male  smoker_yes  region_northwest  \
0   19  27.900         0  16884.92400     False        True             False
1   18  33.770         1   1725.55230      True       False             False
2   28  33.000         3   4449.46200      True       False             False
3   33  22.705         0  21984.47061      True       False              True
4   32  28.880         0   3866.85520      True       False              True

   region_southeast  region_southwest
0             False              True
1              True             False
2              True             False
3             False             False
4             False             False
```

Train a Linear Regression model to predict charges.

[18]:
```
import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression

from sklearn.metrics import mean_squared_error

from sklearn.metrics import mean_squared_error
```

[19]:
```
x = Dataset.drop("charges", axis=1)
y = Dataset["charges"]
```

[20]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
↪random_state=42)
```

[21]:
```
print("Training Data:", x_train.shape)
print("Testing Data:", x_test.shape)
```

```
Training Data: (1070, 8)
Testing Data: (268, 8)
```

[22]:
```
Linear_model = LinearRegression()
Linear_model.fit(x_train, y_train)

y_predict_Linear = Linear_model.predict(x_test)
```

[23]:
```
model = LinearRegression()
model.fit(x_train, y_train)
```

[23]:
```
LinearRegression()
```

Evalute the Model using the MAE RMSE.

Mean Sqaure Error.

[24]:
```
print("Mean Squared Error:", mean_squared_error(y_test, y_predict_Linear))
```

```
Mean Squared Error: 33596915.851361446
```

Root Mean Square Error.

[25]:
```
rmse = np.sqrt(mean_squared_error(y_test, y_predict_Linear))

print("Root Mean Square Error:", rmse)
```

```
Root Mean Square Error: 5796.284659276272
```

[26]:
```
comparison = pd.DataFrame({
    "Actual Charges": y_test.values,
    "Predicted Charges": y_predict_Linear})
```

[27]:
```
comparison.head()
```

[27]:

	Actual Charges	Predicted Charges
0	9095.06825	8969.550274
1	5272.17580	7068.747443
2	29330.98315	36858.410912
3	9301.89355	9454.678501
4	33750.29180	26973.173457

Skills: Regression modeling. Feature correlation and visulaization. Error model performance using MAE and RMSE.

Task Completed. Best Wishes. Zaigham Abbas.