Homework2

February 26, 2024

1 Homework 2

1.1 Section 1: Setup

[ ]:
```
# Dataset: Kaggle
# The data set contains medical insurance costs
# Source:
# https://www.kaggle.com/datasets/mirichoi0218/insurance
# https://www.kaggle.com/datasets/mirichoi0218/insurance/download?
  ↪datasetVersionNumber=1
```

[17]:
```
import pandas as pd
import numpy as np
import statsmodels.api as sm
import statsmodels.stats.outliers_influence as inf
import matplotlib.pyplot as plt
import seaborn as sns

data = pd.read_csv('insurance.csv')
```

[21]:
```
data.head()
```

[21]:

	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

[25]:
```
data.info()
```

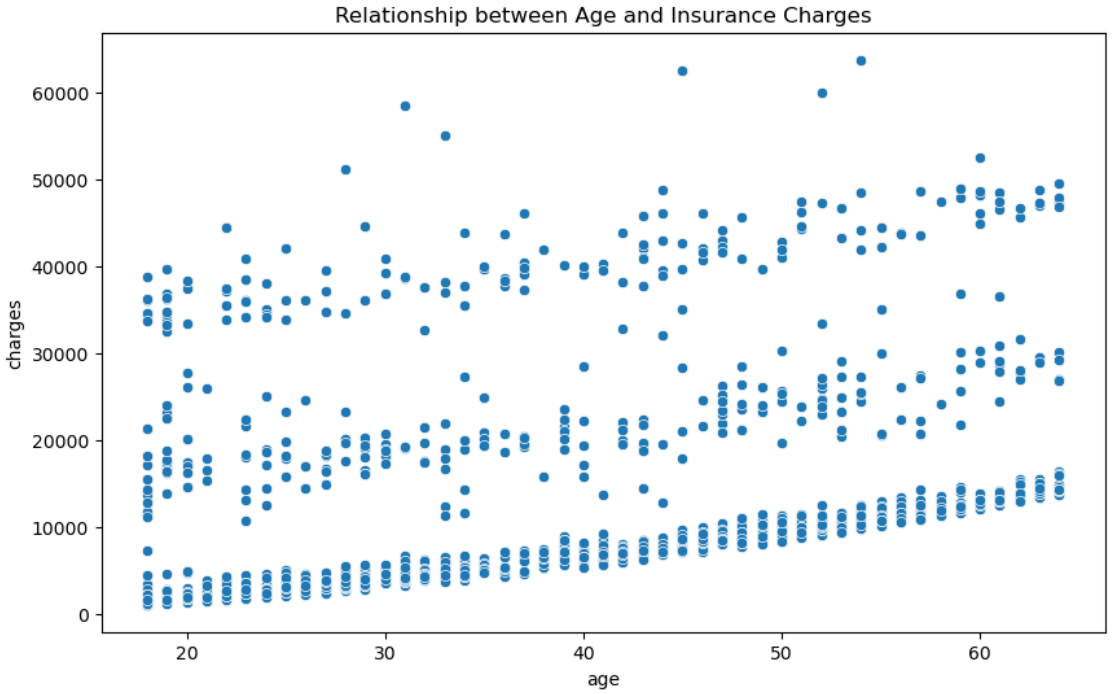
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1338 non-null   int64
 1   sex       1338 non-null   object
```

```
 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
```

[27]:
```
data_points = [
{'age': 18, 'bmi': 30.0, 'charges': 1111.0, },
{'age': 19, 'bmi': 24.0, 'charges': 2111.5, },
{'age': 20, 'bmi': 25.0, 'charges': 7111.0, },
{'age': 21, 'bmi': 23.0, 'charges': 4111.5, },
{'age': 22, 'bmi': 26.0, 'charges': 5111.8, }
]
```

1.2 Section 2: Simple Linear Regression

[46]:
```
X = data['age']
y = data['charges']

plt.figure(figsize=(10,6))
sns.scatterplot(x='age', y='charges', data=data)
plt.title('Relationship between Age and Insurance Charges')
plt.show()
```



[48]:
```
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()

model.summary()
```

[48]:

Dep. Variable:	charges	**R-squared:**	0.089
Model:	OLS	**Adj. R-squared:**	0.089
Method:	Least Squares	**F-statistic:**	131.2
Date:	Mon, 26 Feb 2024	**Prob (F-statistic):**	4.89e-29
Time:	19:39:30	**Log-Likelihood:**	-14415.
No. Observations:	1338	**AIC:**	2.883e+04
Df Residuals:	1336	**BIC:**	2.884e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	3165.8850	937.149	3.378	0.001	1327.440	5004.330
age	257.7226	22.502	11.453	0.000	213.579	301.866

Omnibus:	399.600	**Durbin-Watson:**	2.033
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	864.239
Skew:	1.733	**Prob(JB):**	2.15e-188
Kurtosis:	4.869	**Cond. No.**	124.

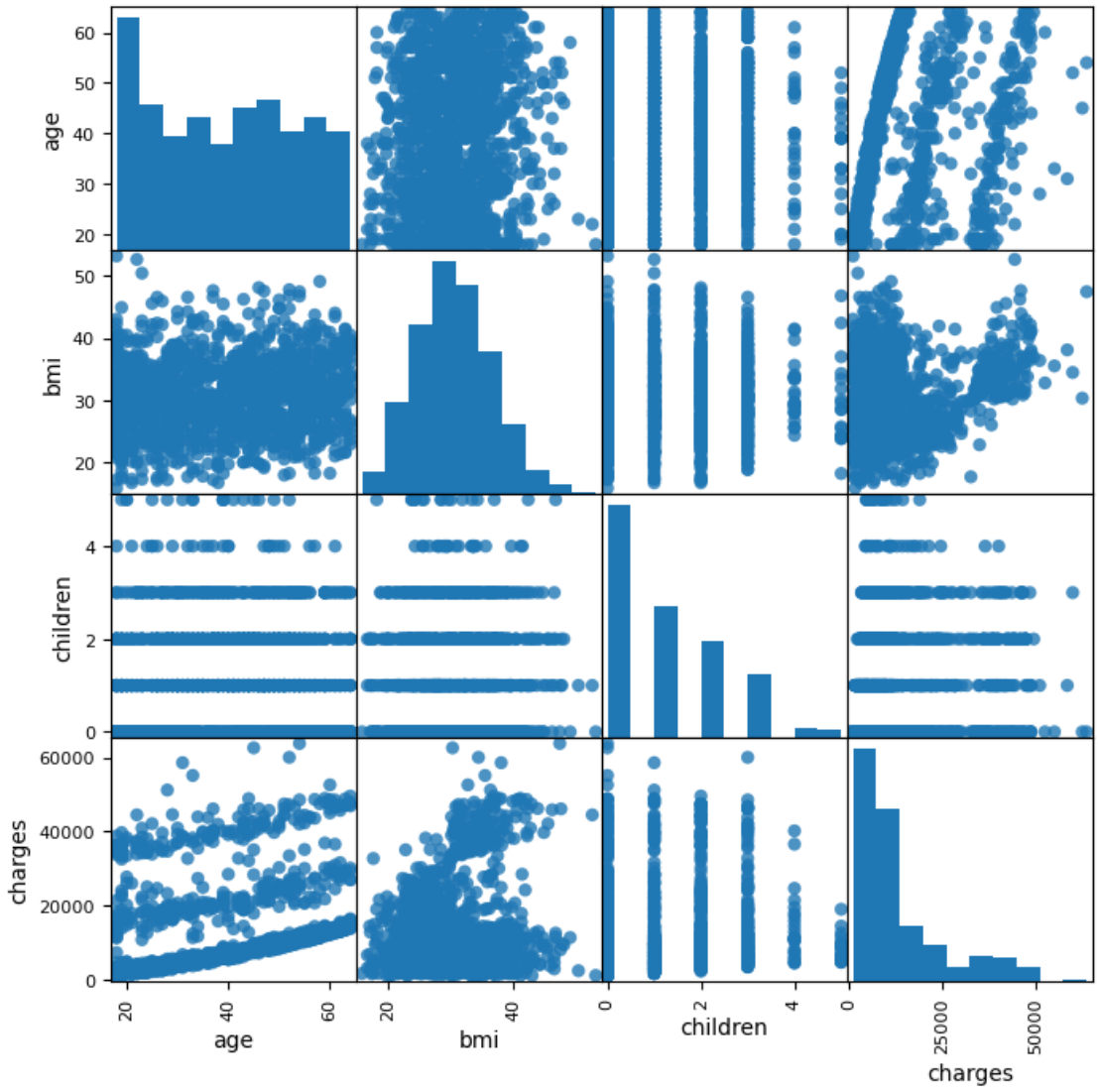
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[52]:
```
# Observations:
# Intercept coefficient: 2165.8850
# Age coefficient: 254.7226. For every one-unit increase in age, the insurance␣
 ↪costs are expected to increase by
# approximately $254.72 units
# R-squared: 0.089. This suggests that approximately 8.9% of the variability ␣
 ↪in the dependent variable, insurance costs,
# can be explained by the model. In simpler terms, the model captures over half␣
 ↪of the
# variability in insurance costs (charges) using age as a predictor.
```

1.3 Section 3: Multicollinearity

[55]:
```
selected_predictors = ['age', 'bmi', 'children', 'charges', 'smoker']
X = data[selected_predictors]
pd.plotting.scatter_matrix(X, figsize=(8, 8), alpha=0.8,␣
 ↪marker='o',diagonal='hist')
```

[55]:
```
array([[<Axes: xlabel='age', ylabel='age'>,
        <Axes: xlabel='bmi', ylabel='age'>,
        <Axes: xlabel='children', ylabel='age'>,
        <Axes: xlabel='charges', ylabel='age'>],
       [<Axes: xlabel='age', ylabel='bmi'>,
        <Axes: xlabel='bmi', ylabel='bmi'>,
        <Axes: xlabel='children', ylabel='bmi'>,
        <Axes: xlabel='charges', ylabel='bmi'>],
       [<Axes: xlabel='age', ylabel='children'>,
        <Axes: xlabel='bmi', ylabel='children'>,
        <Axes: xlabel='children', ylabel='children'>,
        <Axes: xlabel='charges', ylabel='children'>],
       [<Axes: xlabel='age', ylabel='charges'>,
        <Axes: xlabel='bmi', ylabel='charges'>,
        <Axes: xlabel='children', ylabel='charges'>,
        <Axes: xlabel='charges', ylabel='charges'>]], dtype=object)
```



[57]:
```
# Visual Observations:
# - bmi: Displays a possible correlation with both insurance costs and age.
# - age: Seems to correlate with charges and bmi.
# - charges: Indicates a potential correlation with age and bmi.
```

[78]:
```
X_numeric = X.select_dtypes(include=[np.number])

X_filled = X_numeric.fillna(0)  # Or X_numeric.fillna(X.mean())

X_dropped = X_numeric.dropna()

X_no_inf = X_filled.replace([np.inf, -np.inf], np.nan).fillna(0)
```

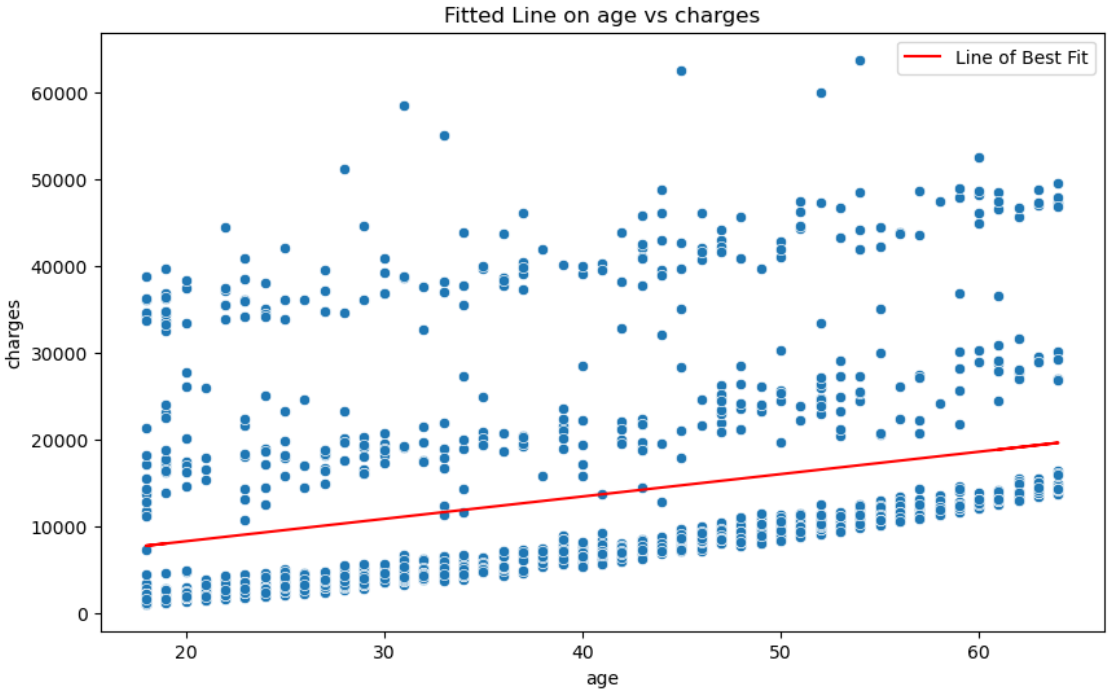
```
X_final = X_no_inf.astype(float)
```

[80]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

for i in range(X_final.shape[1]):
    vif = variance_inflation_factor(X_final.values, i)
    print(f"VIF for {X_final.columns[i]}: \t{vif:10.3f}")
```

```
VIF for age:          8.098
VIF for bmi:          8.044
VIF for children:             1.800
VIF for charges:              2.474
```

1.4 Section 4: Multiple Linear Regression

[99]:
```
age_values = []
for point in data_points:
    age_values.append(point['age'])

beta_1 = model.params['age']
beta_0 = model.params['const']

charge_values = beta_0 + beta_1 * np.array(lstat_values)

plt.figure(figsize=(10,6))
sns.scatterplot(x=data['age'], y=data['charges'])

plt.plot(data['age'], beta_0 + beta_1 * data['age'], color='red',
    label="Line of Best Fit")

sns.scatterplot(x=lstat_values, y=medv_values, color='black', s=100,
    label="Evaluation Points")

plt.title('Fitted Line on age vs charges')
plt.legend()
plt.show()
```



[105]:
```
X = pd.DataFrame(data[['age', 'bmi','charges','children']])
y = data['charges']

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
model.summary()
```

[105]:

Dep. Variable:	charges	**R-squared:**	1.000
Model:	OLS	**Adj. R-squared:**	1.000
Method:	Least Squares	**F-statistic:**	2.193e+33
Date:	Mon, 26 Feb 2024	**Prob (F-statistic):**	0.00
Time:	20:08:24	**Log-Likelihood:**	32996.
No. Observations:	1338	**AIC:**	-6.598e+04
Df Residuals:	1333	**BIC:**	-6.596e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	3.082e-12	7.35e-13	4.194	0.000	1.64e-12	4.52e-12
age	1.199e-14	9.66e-15	1.241	0.215	-6.96e-15	3.09e-14
bmi	-4.13e-14	2.17e-14	-1.906	0.057	-8.38e-14	1.2e-15
charges	1.0000	1.14e-17	8.79e+16	0.000	1.000	1.000
children	-1.137e-13	1.08e-13	-1.057	0.291	-3.25e-13	9.73e-14

Omnibus:	472.843	**Durbin-Watson:**	1.603
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1309.031
Skew:	1.867	**Prob(JB):**	5.59e-285
Kurtosis:	6.088	**Cond. No.**	1.02e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.02e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

[150]:
```
age_values = []
bmi_values = []
children_values = []
charges_values = []
for point in data_points:
    age_values.append(point['age'])
    bmi_values.append(point['bmi'])
    charges_values.append(point['charges'])

beta_0 = model.params['const']
beta_age = model.params['age']
beta_bmi = model.params['bmi']
beta_charges = model.params['charges']

age_values = (beta_0 + beta_age * np.array(age_values) + beta_bmi * np.
 ↪array(bmi_values) + beta_charges * np.array(charges_values))

for i, (age, bmi, children, charges,) in enumerate(zip(age_values, bmi_values,␣
 ↪children_values, charges_values,)):
    print(np.array(age_values).shape)
print(np.array(bmi_values).shape)
print(np.array(charges_values).shape)
print(beta_age, beta_bmi, beta_children, beta_charges)
```

```
(5,)
(5,)
1.199040866595169e-14 -4.1300296516055823e-14 -1.1368683772161603e-13
0.9999999999999997
```

[ ]: