

hw4_project

February 6, 2026

```
[1]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import statsmodels.api as sm
from scipy.stats import norm
```

```
[2]: insurance = pd.read_csv("../datasets/insurance.csv")
insurance.head()
```

```
[2]:   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
```

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```
[3]: # continuous predictor variables only
X = insurance[['age', 'bmi', 'children']]
y = insurance['charges']

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

OLS Regression Results

```
=====
Dep. Variable:          charges    R-squared:                0.120
Model:                  OLS      Adj. R-squared:            0.118
Method:                 Least Squares    F-statistic:         60.69
Date:                  Fri, 06 Feb 2026    Prob (F-statistic):    8.80e-37
Time:                  10:18:53    Log-Likelihood:       -14392.
No. Observations:      1338    AIC:                  2.879e+04
Df Residuals:          1334    BIC:                  2.881e+04
Df Model:               3
Covariance Type:        nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
-----	-----	-----	-----	-----	-----	-----
const	-6916.2433	1757.480	-3.935	0.000	-1.04e+04	-3468.518
age	239.9945	22.289	10.767	0.000	196.269	283.720
bmi	332.0834	51.310	6.472	0.000	231.425	432.741
children	542.8647	258.241	2.102	0.036	36.261	1049.468
=====	=====	=====	=====	=====	=====	=====
Omnibus:		325.395	Durbin-Watson:			2.012
Prob(Omnibus):		0.000	Jarque-Bera (JB):			603.372
Skew:		1.520	Prob(JB):			9.54e-132
Kurtosis:		4.255	Cond. No.			290.
=====	=====	=====	=====	=====	=====	=====

Notes:

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

We see that the DW score is 2, which doesn't indicate any signs of autocorrelation or nonlinearity. The omnibus, skew, and kurtosis scores are quite high however, indicating non-Gaussian residuals. Overall, however, as noted in the previous project as well, this doesn't indicate an ill-fitted *non-linear* relationship, but rather just an omission of more important predictor variables such as the categorical ones that Lantz analyzes is more important towards the model.

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```
[6]: X = insurance.drop(columns=['charges'])
X = pd.get_dummies(X, drop_first=True).astype(float)
y = insurance['charges']

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

OLS Regression Results

Dep. Variable:	charges	R-squared:	0.751
Model:	OLS	Adj. R-squared:	0.749
Method:	Least Squares	F-statistic:	500.8
Date:	Fri, 06 Feb 2026	Prob (F-statistic):	0.00
Time:	10:24:23	Log-Likelihood:	-13548.
No. Observations:	1338	AIC:	2.711e+04
Df Residuals:	1329	BIC:	2.716e+04
Df Model:	8		
Covariance Type:	nonrobust		
=====	=====	=====	=====

```
=====
coef      std err      t      P>|t|      [0.025      0.975]
```

```

-----
----
const          -1.194e+04    987.819    -12.086    0.000    -1.39e+04
-1e+04
age             256.8564     11.899     21.587    0.000     233.514
280.199
bmi             339.1935     28.599     11.860    0.000     283.088
395.298
children        475.5005     137.804      3.451    0.001     205.163
745.838
sex_male        -131.3144     332.945     -0.394    0.693    -784.470
521.842
smoker_yes      2.385e+04     413.153     57.723    0.000     2.3e+04
2.47e+04
region_northwest -352.9639     476.276     -0.741    0.459    -1287.298
581.370
region_southeast -1035.0220     478.692     -2.162    0.031    -1974.097
-95.947
region_southwest -960.0510     477.933     -2.009    0.045    -1897.636
-22.466
=====
Omnibus:                300.366    Durbin-Watson:                2.088
Prob(Omnibus):           0.000    Jarque-Bera (JB):             718.887
Skew:                    1.211    Prob(JB):                     7.86e-157
Kurtosis:                5.651    Cond. No.                     311.
=====

```

Notes:

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

This is a better model including all variables. We can see that only `age`, `bmi`, `children`, and `smoker_yes` are significant predictors. Likewise to Lantz, we can convert `bmi` to a categorical binary predictor instead, indicating 1 for individuals that are obese (`bmi > 30`), and 0 otherwise.

```

[8]: # model with only significant predictors
X = insurance.drop(columns=['charges'])
X = pd.get_dummies(X, drop_first=True).astype(float)
X = X[['age', 'bmi', 'children', 'smoker_yes']]

# convert bmi to categorical variable (obese or not)
X['bmi_obese'] = (X['bmi'] >= 30).astype(float)
X = X.drop(columns=['bmi'])

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

```

OLS Regression Results

```

=====
Dep. Variable:          charges    R-squared:          0.753
Model:                  OLS        Adj. R-squared:      0.753
Method:                 Least Squares    F-statistic:        1018.
Date:                  Fri, 06 Feb 2026    Prob (F-statistic): 0.00
Time:                  10:28:54    Log-Likelihood:     -13541.
No. Observations:      1338    AIC:                2.709e+04
Df Residuals:          1333    BIC:                2.712e+04
Df Model:               4
Covariance Type:       nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const      -4549.7577      531.337      -8.563      0.000     -5592.105     -3507.410
age         260.3762       11.783      22.097      0.000       237.261       283.492
children    475.9851       136.795       3.480      0.001       207.628       744.342
smoker_yes  2.383e+04      408.245     58.366      0.000      2.3e+04      2.46e+04
bmi_obese   4184.2284      331.129     12.636      0.000      3534.637      4833.820
=====
Omnibus:            327.599    Durbin-Watson:        2.092
Prob(Omnibus):      0.000    Jarque-Bera (JB):     831.658
Skew:               1.293    Prob(JB):             2.56e-181
Kurtosis:           5.869    Cond. No.             140.
=====

```

Notes:

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

This model doesn't really improve anything. We can try again by adding an `age^2` term and interaction between obesity and smoking like Lantz does.

```

[13]: X = insurance.drop(columns=['charges'])
X = pd.get_dummies(X, drop_first=True).astype(float)
X = X[['age', 'bmi', 'children', 'smoker_yes']]
X['bmi_obese'] = (X['bmi'] >= 30).astype(float)
X = X.drop(columns=['bmi'])
X['age_squared'] = X['age'] ** 2
X['obese_smoker'] = X['bmi_obese'] * X['smoker_yes']
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
print(model.summary())

```

OLS Regression Results

```

=====
Dep. Variable:          charges    R-squared:          0.864
Model:                  OLS        Adj. R-squared:      0.863
Method:                 Least Squares    F-statistic:        1404.
Date:                  Fri, 06 Feb 2026    Prob (F-statistic): 0.00

```

Time: 10:33:28 Log-Likelihood: -13145.
 No. Observations: 1338 AIC: 2.630e+04
 Df Residuals: 1331 BIC: 2.634e+04
 Df Model: 6
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	2237.3818	1083.910	2.064	0.039	111.023	4363.741
age	-24.5114	60.287	-0.407	0.684	-142.779	93.757
children	669.3870	106.688	6.274	0.000	460.092	878.682
smoker_yes	1.339e+04	442.587	30.253	0.000	1.25e+04	1.43e+04
bmi_obese	42.3927	276.907	0.153	0.878	-500.828	585.614
age_squared	3.6643	0.752	4.870	0.000	2.188	5.140
obese_smoker	1.976e+04	608.631	32.465	0.000	1.86e+04	2.1e+04
Omnibus:	880.074	Durbin-Watson:	2.062			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	7491.608			
Skew:	3.125	Prob(JB):	0.00			
Kurtosis:	12.763	Cond. No.	1.84e+04			

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.84e+04. This might indicate that there are strong multicollinearity or other numerical problems.

3 3

This is a much better model than our one from project 3. The R^2 is significantly higher.

Comparing the coefficients:

Intercept: 2237.3818, SE 1083.910, p 0.039

Still significant, albeit with a completely different value. No big change.

Age: 024.5114, SE 60.287, p 0.684

Age has now become a statistically insignificant predictor. This is expected as we now added in an age^2 term.

We now have additional coefficients such as `smoker_yes`, `bmi_obese`, and `obese_smoker`. These coefficients are all relatively well estimated and statistically significant with the exception of `bmi_obese`.

```
[ ]: X = insurance.drop(columns=['charges'])
y = insurance['charges']
X = pd.get_dummies(X, drop_first=True).astype(float)
X['age_squared'] = X['age'] ** 2
X['bmi_obese'] = (X['bmi'] >= 30).astype(float)
```

```
X['obese_smoker'] = X['bmi_obese'] * X['smoker_yes']
X = sm.add_constant(X)
model = sm.OLS(y, X).fit()
print(model.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          charges    R-squared:                0.866
Model:                  OLS        Adj. R-squared:            0.865
Method:                 Least Squares    F-statistic:            781.7
Date:                  Fri, 06 Feb 2026    Prob (F-statistic):      0.00
Time:                  12:25:25    Log-Likelihood:         -13131.
No. Observations:      1338    AIC:                    2.629e+04
Df Residuals:          1326    BIC:                    2.635e+04
Df Model:               11
Covariance Type:        nonrobust
=====
```

```
=====
=====
              coef      std err          t      P>|t|      [0.025
0.975]
-----
----
const          134.2509    1362.751      0.099      0.922    -2539.132
2807.634
age           -32.6851      59.824     -0.546      0.585    -150.045
84.675
bmi            120.0196     34.266      3.503      0.000      52.798
187.241
children       678.5612    105.883      6.409      0.000      470.844
886.278
sex_male      -496.8245     244.366     -2.033      0.042    -976.210
-17.438
smoker_yes     1.34e+04     439.949     30.469      0.000     1.25e+04
1.43e+04
region_northwest -279.2038    349.275     -0.799      0.424    -964.395
405.987
region_southeast -828.5467    351.635     -2.356      0.019    -1518.369
-138.725
region_southwest -1222.6437    350.528     -3.488      0.001    -1910.294
-534.993
age_squared      3.7316        0.746      5.000      0.000         2.268
5.196
bmi_obese     -1000.1403     422.840     -2.365      0.018    -1829.649
-170.632
obese_smoker    1.981e+04     604.657     32.764      0.000     1.86e+04
2.1e+04
=====
```

```
Omnibus:                890.976    Durbin-Watson:                2.064
```

Prob(Omnibus):	0.000	Jarque-Bera (JB):	7722.759
Skew:	3.170	Prob(JB):	0.00
Kurtosis:	12.916	Cond. No.	2.34e+04

=====

Notes:

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

[2] The condition number is large, 2.34e+04. This might indicate that there are strong multicollinearity or other numerical problems.

We can also generate a model similar to Lantz's final model and find similar results. There are varying degrees of statistical significance between the added coefficients, however overall model performance is the same.

Adding in the age^2 term and interaction effects between obesity indication and smoking have significantly improved our model compared to just using the continuous predictor variables.

LLM Usage: All work was done by myself in VSCode with [GitHub Copilot integration](#). The integration “provides code suggestions, explanations, and automated implementations based on natural language prompts and existing code context,” and also offers autonomous coding and an in-IDE chat interface that is able to interact with the current codebase. Only the Copilot provided automatic inline suggestions for both LaTeX and Python in `.tex` and `.ipynb` Jupyter notebook files respectively were taken into account / used.