Insurance Cost Analysis Project

Background Information

Insurance companies are always interested in how they can maximize their profit based on the risk level of their customers. In this analysis I will be creating a predictive neural network based on the data provided from this Kaggle Page in order to accurately predict how much a customer should be charged based on the given explanatory variables. Furthermore, I will be creating a linear/logistic regression model to determine which variable is most significantly affecting the charges of the customer.

Imports

```
import tensorflow as tf
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
import seaborn as sns
import statsmodels.formula.api as smf
from sklearn.metrics import r2_score
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
```

Reading the dataset into pandas

```
insurance = pd.read_csv("https://raw.githubusercontent.com/stedy/Machine-Learning-with-R-datasets/refs/heads/master/insurance.csv")
insurance
```

	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
...	...	...	...	...	...	...	...
1333	50	male	30.970	3	no	northwest	10600.54830
1334	18	female	31.920	0	no	northeast	2205.98080
1335	18	female	36.850	0	no	southeast	1629.83350
1336	21	female	25.800	0	no	southwest	2007.94500
1337	61	female	29.070	0	yes	northwest	29141.36030

1338 rows × 7 columns

Note: The data contains string values which the model will not be able to process; therefore, the data values will be one-hot encoded.

```
# One-hot encoding the data
insurance_one_hot_encoded = pd.get_dummies(insurance, dtype = int)
```

Creating the training and test datasets

```
# Separating explanatory variables (expvar) and response (charges)
expvar = insurance_one_hot_encoded.drop("charges", axis = 1)
charges = insurance_one_hot_encoded["charges"]
expvar_train, expvar_test, charges_train, charges_test = train_test_split(expvar, charges, test_size = .2, random_state = 10) # random_state
len(expvar_test) / len(expvar) # Make sure the split worked
```

```
0.20029895366218237
```

Creating a basic neural network model

This first model will have 1 layer, use SGD as its optimizer, and run for 100 epochs.

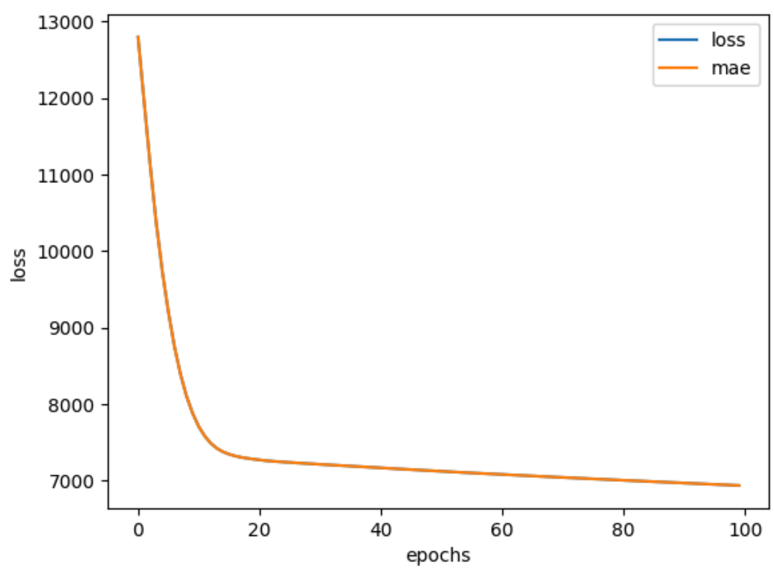
```
# Set random seed (for reproducibility)
tf.random.set_seed(10)

# 1. Create the model
insurance_model_1 = tf.keras.Sequential([
    tf.keras.layers.Dense(1)
])

# 2. Compile the model
insurance_model_1.compile(loss = tf.keras.losses.mae,
                          optimizer = tf.keras.optimizers.SGD(),
                          metrics = ["mae"])

# 3. Fit the model
history = insurance_model_1.fit(expvar_train, charges_train, epochs = 100, verbose = 0) # verbose = 0 to reduce clutter, since I will be eva
```

```
# Evaluating the model
insurance_model_1.evaluate(expvar_test, charges_test)
```

```
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 6816.2783 - mae: 6816.2783
[7177.03076171875, 7177.03076171875]
```

```
# Plotting the loss
pd.DataFrame(history.history).plot()
plt.ylabel("loss")
plt.xlabel("epochs")
```

```
Text(0.5, 0, 'epochs')
```



Making a function

Now to, hopefully, expedite the process of creating multiple models and evaluating them, I will create a function to:

1. Create the models
2. Report the MAE of the evaluation using the test data
3. Plot the loss over time.

```
# Model Creating Function

def create_neural_network(seed = 10, # sets random seed to 10 by default
                   num_layers = 0, # adds 0 additional hidden layers
                   num_units = 0, # sets number of units in additional hidden layers to 0
```

```
                  optimizer = "SGD", # sets optimizer to SGD by default
                  learning_rate = .001, # sets learning_rate if using Adam optimizer
                  epochs = 100): # epochs is set to 100 by default
  """
  A function that creates a neural network with num_layers additional hidden layers, each of which has num_units hidden units. The optimizer
  """
  tf.random.set_seed(seed)

  # 1. Create dummy model
  dummy_model = tf.keras.Sequential([])

  # 2. Add hidden layers
  for i in range(num_layers):
    dummy_model.add(tf.keras.layers.Dense(num_units))
  dummy_model.add(tf.keras.layers.Dense(1))

  # 3. Compile the model
  if optimizer == "SGD":
    dummy_model.compile(loss = tf.keras.losses.mae,
                        optimizer = tf.keras.optimizers.SGD(),
                        metrics = ["mae"])
  else:
    dummy_model.compile(loss = tf.keras.losses.mae,
                        optimizer = tf.keras.optimizers.Adam(learning_rate = learning_rate),
                        metrics = ["mae"])

  # 4. Fit the model
  history = dummy_model.fit(expvar_train, charges_train, epochs = epochs, verbose = 0) # This function is specific to this project so it wil

  # 5. Evaluate the model
  test_mae = dummy_model.evaluate(expvar_test, charges_test)

  # 6. Plot the loss over time
  pd.DataFrame(history.history).plot()
  plt.xlabel("epochs")
  plt.ylabel("loss")

  # 7. Return evaluation metric
  print(test_mae)
```

Improving the model

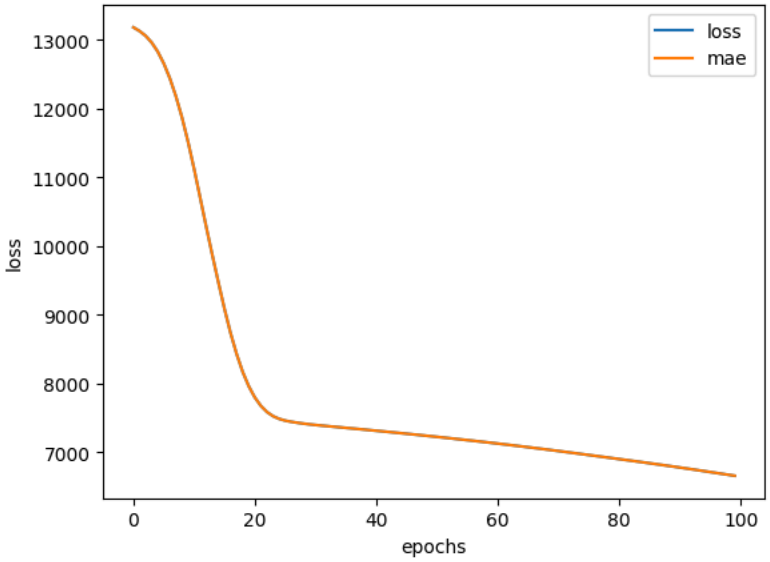
The first model is never the best, so now I will attempt to create 3 more models that will (hopefully) have improved performance.

- `Model 2` : 1 add. hidden layer with 100 units, 100 epochs
- `Model 3` : Same as `Model 2` but with 200 epochs
- `Model 4` : 2 add. hidden layers with 100 units, 100 epochs

Optimizer: If necessary the optimizer will be changed to Adam if SGD is unable to return an MAE value.

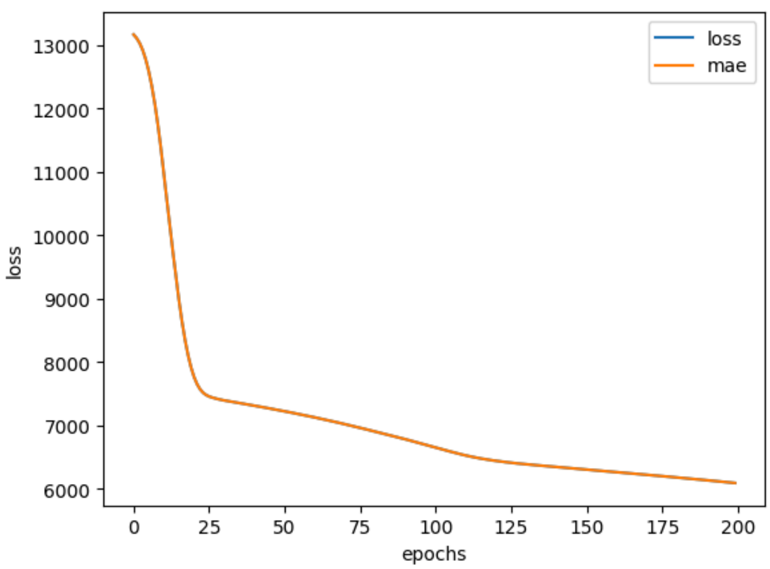
```
# Creating Model 2
insurance_model_2 = create_neural_network(num_layers = 1, num_units = 100, optimizer = "Adam") # The model seemed to struggle to learn using
```

```
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 6521.8691 - mae: 6521.8691
[6885.44677734375, 6885.44677734375]
```



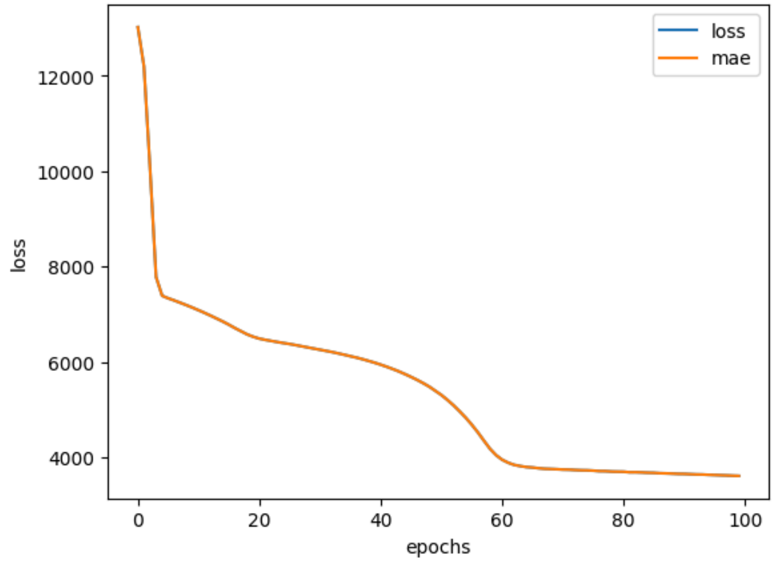

```
# Creating Model 3
insurance_model_3 = create_neural_network(num_layers = 1, num_units = 100, optimizer = "Adam", epochs = 200) # The model seemed to struggle
```

```
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 5965.7827 - mae: 5965.7827
[6336.0615234375, 6336.0615234375]
```




```
# Creating Model 4
insurance_model_4 = create_neural_network(num_layers = 2, num_units = 100, optimizer = "Adam", epochs = 100) # The model seemed to struggle
```

```
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 3702.6672 - mae: 3702.6672
[3872.36767578125, 3872.36767578125]
```

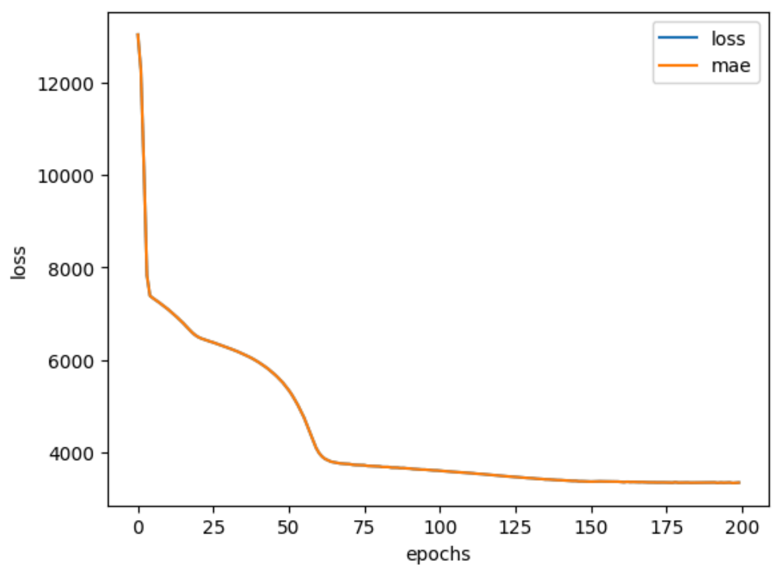


Best performing model so far

`Model 4` performed the best with an MAE of ~3700. The model's learning appeared to drop-off drastically at 60 epochs, but there is definite decrease until 100 epochs. Therefore, it could be said that 200 epochs would result in an even better MAE, which I will be testing.

```
# Enhancing Model 4
insurance_model_4_enhanced = create_neural_network(num_layers = 2, num_units = 100, optimizer = "Adam", epochs = 200) # Same as Model 4, but
```

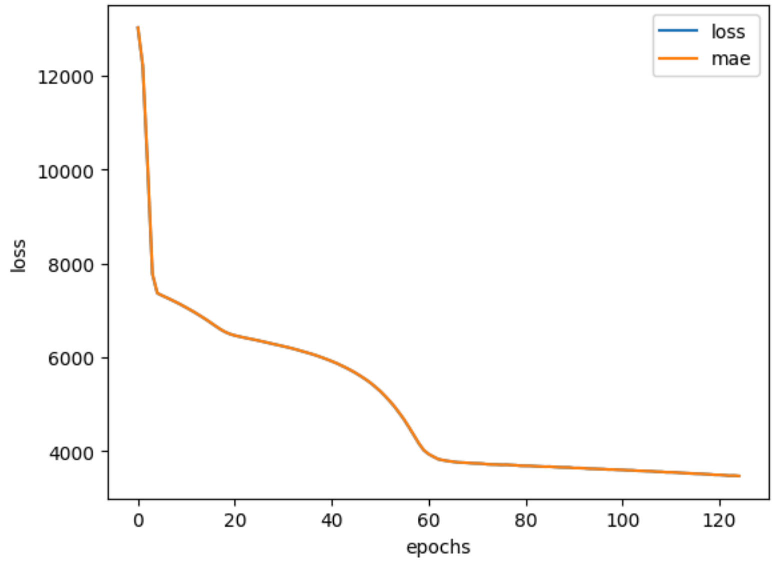
```
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 3862.8740 - mae: 3862.8740
[3881.950439453125, 3881.950439453125]
```



Too many epochs! The tail-end of the graph shows a slight increase in MAE, possibly a result of the model overfitting for the training data. Around 125 epochs seems to still be decreasing... time to test it.

```
insurance_model_4_enhanced_2 = create_neural_network(num_layers = 2, num_units = 100, optimizer = "Adam", epochs = 125) # Reducing number of
```

```
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 3798.8689 - mae: 3798.8689
[3894.418212890625, 3894.418212890625]
```



Neural Network Conclusions

Despite trying to optimize the number of epochs manually, insurance_model_4 seems to perform the best compared to either of its 'enhanced' counterparts. The final, best model (Model 4) has an MAE of ~3700 with 2 additional hidden layers each with 100 hidden units. It uses the Adam optimizer with the default learning rate and runs for 100 epochs.

Additional Notes:

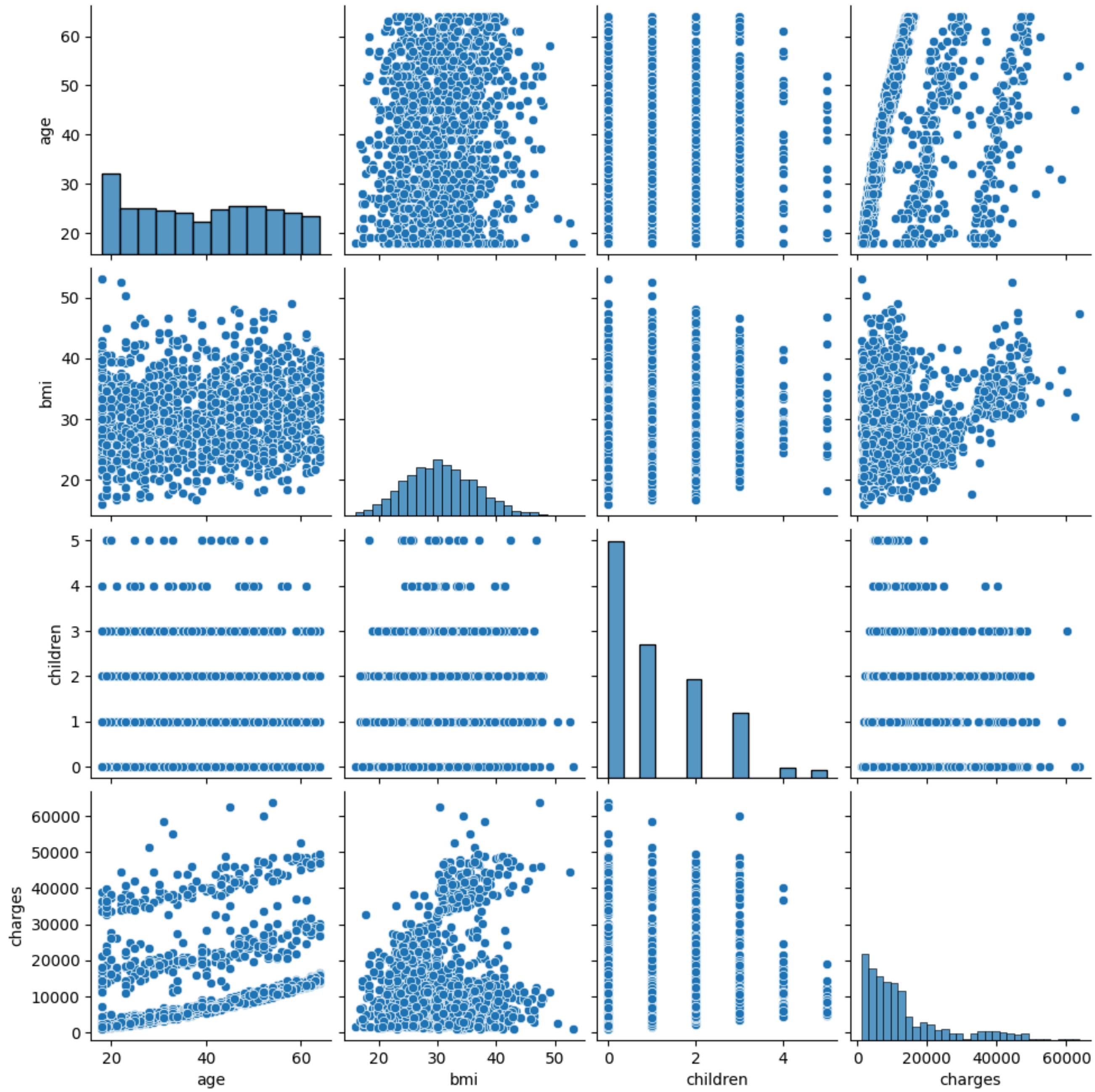
1. Early Stopping Callback (or other methods) can be used to better optimize the number of epochs the model runs compared to guessing based on the loss graph. *Although this will not be explored in this project.*
2. The training and test data is not Normalized or Standardized which could further improve the MAE value and should be tested.
3. Only 6 neural networks were created. There is a decent likelihood that changing the number of additional hidden layers and the number of hidden units could reduce the MAE further.
4. The function used to create the neural networks, while handy, does not allow for additional hidden layers to have a different number of hidden units. This means the optimization of the neural network is slightly one-dimensional when it comes to changing the number of hidden layers and units.

For the Linear Regression Model:

1. Use a Backwards Elimination Algorithm to determine which model has the greatest R^2 value.
2. Make sure the model satisfies the linearity assumption.

```
sns.pairplot(insurance) # Pairplot of all the variables
```

```
<seaborn.axisgrid.PairGrid at 0x7eac289c1290>
```



Note: Visually, there do not seem to be any explanatory variables that have a significant effect on how much the charges are (although having more than 3 children seems to lead to lower charges).

```
insurance_one_hot_encoded # to check the var names
```

	age	bmi	children	charges	sex_female	sex_male	smoker_no	smoker_yes	region_northeast	region_northwest	region_southeas
0	19	27.900	0	16884.92400	1	0	0	1	0	0	
1	18	33.770	1	1725.55230	0	1	1	0	0	0	
2	28	33.000	3	4449.46200	0	1	1	0	0	0	
3	33	22.705	0	21984.47061	0	1	1	0	0	1	
4	32	28.880	0	3866.85520	0	1	1	0	0	1	
...	...	...	...	...	...	...	...	...	...	...	
1333	50	30.970	3	10600.54830	0	1	1	0	0	1	
1334	18	31.920	0	2205.98080	1	0	1	0	1	0	
1335	18	36.850	0	1629.83350	1	0	1	0	0	0	
1336	21	25.800	0	2007.94500	1	0	1	0	0	0	
1337	61	29.070	0	29141.36030	1	0	0	1	0	1	

1338 rows × 12 columns

```
insurance_full_model_linreg = smf.ols(formula='charges~age+bmi+children+sex_female+sex_male+smoker_no+smoker_yes+region_northeast+region_nor
insurance_full_model_linreg.summary()
```

OLS Regression Results

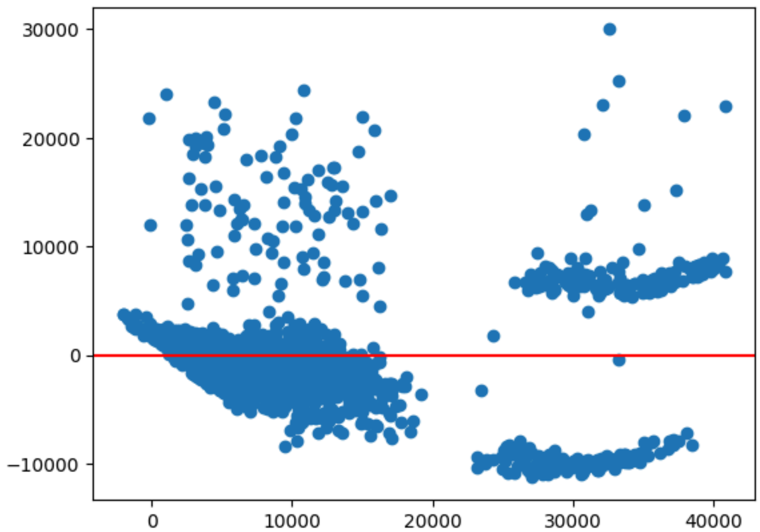
Dep. Variable:	charges	**R-squared:**	0.751
Model:	OLS	**Adj. R-squared:**	0.749
Method:	Least Squares	**F-statistic:**	500.8
Date:	Tue, 28 Jan 2025	**Prob (F-statistic):**	0.00
Time:	01:19:56	**Log-Likelihood:**	-13548.
No. Observations:	1338	**AIC:**	2.711e+04
Df Residuals:	1329	**BIC:**	2.716e+04
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-296.4168	430.507	-0.689	0.491	-1140.964	548.130
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_female	-82.5512	269.226	-0.307	0.759	-610.706	445.604
sex_male	-213.8656	274.976	-0.778	0.437	-753.299	325.568
smoker_no	-1.207e+04	282.338	-42.759	0.000	-1.26e+04	-1.15e+04
smoker_yes	1.178e+04	313.530	37.560	0.000	1.12e+04	1.24e+04
region_northeast	512.9050	300.348	1.708	0.088	-76.303	1102.113
region_northwest	159.9411	301.334	0.531	0.596	-431.201	751.083
region_southeast	-522.1170	330.759	-1.579	0.115	-1170.983	126.749
region_southwest	-447.1459	310.933	-1.438	0.151	-1057.119	162.827

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.**	6.51e+17

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 8.3e-30. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

```
# scatter plot of the residuals
plt.scatter(insurance_full_model_linreg.fittedvalues, insurance_full_model_linreg.resid)
plt.axhline(y=0, color='r')
plt.show()
```



The model's residuals seem to have an even spread above and below the x-axis, therefore it meets the linearity assumption.

Creating predictive models using Backwards Elimination

```
insurance_train, insurance_test = train_test_split(insurance_one_hot_encoded, test_size=.2, random_state=10) # splitting the data to test th
len(insurance_test) / len(insurance_one_hot_encoded) # check split
```

```
0.20029895366218237
```

```
insurance_train
```

	age	bmi	children	charges	sex_female	sex_male	smoker_no	smoker_yes	region_northeast	region_northwest	region_southeas
559	19	35.530	0	1646.42970	0	1	1	0	0	1	(
273	50	27.455	1	9617.66245	0	1	1	0	1	0	(
471	18	30.115	0	2203.47185	1	0	1	0	1	0	(
22	18	34.100	0	1137.01100	0	1	1	0	0	0	'
939	53	29.480	0	9487.64420	0	1	1	0	0	0	'
...	...	...	...	...	...	...	...	...	...	...	..
1180	42	41.325	1	7650.77375	1	0	1	0	1	0	(
1147	20	31.920	0	2261.56880	1	0	1	0	0	1	(
527	51	25.800	1	9861.02500	1	0	1	0	0	0	(
1149	42	34.100	0	5979.73100	0	1	1	0	0	0	(
1289	44	34.320	1	7147.47280	0	1	1	0	0	0	'

1070 rows × 12 columns

```
# scaling the training data and making a data frame
scaler = StandardScaler()
scaled_train_data = scaler.fit_transform(insurance_train)
df_train_scaled = pd.DataFrame(scaled_train_data, columns = insurance_train.columns)
df_train_scaled
```

	age	bmi	children	charges	sex_female	sex_male	smoker_no	smoker_yes	region_northeast	region_northwest	region_sc
0	-1.423960	0.784788	-0.899332	-0.949383	-0.987000	0.987000	0.504377	-0.504377	-0.575192	1.774059	-(
1	0.767917	-0.529475	-0.071916	-0.294360	-0.987000	0.987000	0.504377	-0.504377	1.738550	-0.563679	-(
2	-1.494665	-0.096542	-0.899332	-0.903609	1.013171	-1.013171	0.504377	-0.504377	1.738550	-0.563679	-(
3	-1.494665	0.552045	-0.899332	-0.991244	-0.987000	0.987000	0.504377	-0.504377	-0.575192	-0.563679	
4	0.980034	-0.199892	-0.899332	-0.305044	-0.987000	0.987000	0.504377	-0.504377	-0.575192	-0.563679	
...	...	...	...	...	...	...	...	...	...	...	
1065	0.202271	1.727966	-0.071916	-0.455986	1.013171	-1.013171	0.504377	-0.504377	1.738550	-0.563679	-(
1066	-1.353254	0.197235	-0.899332	-0.898835	1.013171	-1.013171	0.504377	-0.504377	-0.575192	1.774059	-(
1067	0.838622	-0.798838	-0.071916	-0.274362	1.013171	-1.013171	0.504377	-0.504377	-0.575192	-0.563679	-(
1068	0.202271	0.552045	-0.899332	-0.593301	-0.987000	0.987000	0.504377	-0.504377	-0.575192	-0.563679	-(
1069	0.343682	0.587852	-0.071916	-0.497344	-0.987000	0.987000	0.504377	-0.504377	-0.575192	-0.563679	

1070 rows × 12 columns

```
# scaling the test data and making a data frame
scaler2 = StandardScaler()
scaled_test_data = scaler2.fit_transform(insurance_test)
df_test_scaled = pd.DataFrame(scaled_test_data, columns = insurance_test.columns)
df_test_scaled
```

	age	bmi	children	charges	sex_female	sex_male	smoker_no	smoker_yes	region_northeast	region_northwest	region_sou
0	-0.181626	-0.465506	1.573706	-0.529499	1.0	-1.0	0.519752	-0.519752	-0.525538	1.732051	-0.
1	-0.254932	-0.610518	-0.946732	-0.699534	1.0	-1.0	0.519752	-0.519752	-0.525538	1.732051	-0.
2	1.431123	1.121988	-0.106586	-0.101755	-1.0	1.0	0.519752	-0.519752	-0.525538	-0.577350	-0.
3	1.577736	-0.916653	-0.946732	0.925534	1.0	-1.0	0.519752	-0.519752	-0.525538	-0.577350	1.
4	-0.768080	-0.755529	-0.946732	-0.828842	1.0	-1.0	0.519752	-0.519752	-0.525538	1.732051	-0.
...	...	...	...	...	...	...	...	...	...	...	
263	0.771362	0.630136	0.733560	2.474477	-1.0	1.0	-1.923994	1.923994	-0.525538	-0.577350	-0.
264	-0.988000	1.645216	-0.946732	-0.874035	1.0	-1.0	0.519752	-0.519752	-0.525538	1.732051	-0.
265	-1.501147	-0.546068	0.733560	0.755013	-1.0	1.0	0.519752	-0.519752	-0.525538	1.732051	-0.
266	1.284509	1.774115	-0.946732	-0.167691	-1.0	1.0	0.519752	-0.519752	1.902811	-0.577350	-0.
267	0.184908	0.930335	0.733560	-0.539731	-1.0	1.0	0.519752	-0.519752	-0.525538	-0.577350	1.

268 rows × 12 columns

Non-Regularized Linear Regression Full Model

```
train_expvar = df_train_scaled.drop('charges', axis=1) # only the explanatory variables of the training data
train_target = df_train_scaled['charges'] # the target variable

test_expvar = df_test_scaled.drop('charges', axis=1) # only the explanatory variables of the test data
test_target = df_test_scaled['charges'] # target variable

linreg = LinearRegression() # instantiating the Linear Regression model
linreg.fit(train_expvar, train_target) # fitting the model with training data
linreg.score(test_expvar, test_target) # checking R^2 value with test data
```

```
0.6969180450282757
```

Backwards Elimination Algorithm

1. Make multiple Linear Regression models while removing one explanatory variable
2. Check each models' R^2 value
3. Select the best model

```
# check variable names
train_expvar
```

	age	bmi	children	sex_female	sex_male	smoker_no	smoker_yes	region_northeast	region_northwest	region_southeast	r
0	-1.423960	0.784788	-0.899332	-0.987000	0.987000	0.504377	-0.504377	-0.575192	1.774059	-0.605425	
1	0.767917	-0.529475	-0.071916	-0.987000	0.987000	0.504377	-0.504377	1.738550	-0.563679	-0.605425	
2	-1.494665	-0.096542	-0.899332	1.013171	-1.013171	0.504377	-0.504377	1.738550	-0.563679	-0.605425	
3	-1.494665	0.552045	-0.899332	-0.987000	0.987000	0.504377	-0.504377	-0.575192	-0.563679	1.651733	
4	0.980034	-0.199892	-0.899332	-0.987000	0.987000	0.504377	-0.504377	-0.575192	-0.563679	1.651733	
...	...	...	...	...	...	...	...	...	...	...	
1065	0.202271	1.727966	-0.071916	1.013171	-1.013171	0.504377	-0.504377	1.738550	-0.563679	-0.605425	
1066	-1.353254	0.197235	-0.899332	1.013171	-1.013171	0.504377	-0.504377	-0.575192	1.774059	-0.605425	
1067	0.838622	-0.798838	-0.071916	1.013171	-1.013171	0.504377	-0.504377	-0.575192	-0.563679	-0.605425	
1068	0.202271	0.552045	-0.899332	-0.987000	0.987000	0.504377	-0.504377	-0.575192	-0.563679	-0.605425	