```
### Homework 5
### Anthony Martinez | amm180005

### Step 1: Description

This notebook performs regression to estim
various features.

### Step 2: Load the data

* upload the data
* put the data in a pandas dataframe
* output the data shape (rows, cols)
* output the first few rows of the data
```

Homework 5

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Step 1: Description

This notebook performs regression to estimate the price of a car given various features.

Step 2: Load the data

- upload the data
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- output the first few rows of the data

```
# load the csv file up into the cloud
import numpy as np
import pandas as pd
import io
import seaborn as sb

from google.colab import files
uploaded = files.upload()
```

Choose Files audi.csv

- **audi.csv**(text/csv) - 534071 bytes, last modified: 2/16/2022 - 100% done

```
Saving audi.csv to audi.csv
```

```
# put the data in a pandas datafram
df = pd.read_csv(io.BytesIO(uploaded['audi.csv']))

# output the data shape
df.shape

# output the first few rows of the data
df.head()
```

	model	year	price	transmission	mileage	fuelType	tax	mpg	engineSize
0	A1	2017	12500	Manual	15735	Petrol	150	55.4	1.4
1	A6	2016	16500	Automatic	36203	Diesel	20	64.2	2.0

Step 3 Data Exploration

```
df.dtypes
```

```
model            object
year              int64
price             int64
transmission     object
mileage           int64
fuelType         object
tax               int64
mpg             float64
engineSize      float64
dtype: object
```

```
# change categorical column type from object to category
df = df.astype({"model":'category', "transmission":"category", "fuelType":"category"})
df.dtypes
```

```
model           category
year               int64
price              int64
transmission    category
mileage            int64
fuelType        category
tax                int64
mpg              float64
engineSize       float64
dtype: object
```

```
# check for NAs
df.isna().sum() # check if na over entier DF in one line of code
```

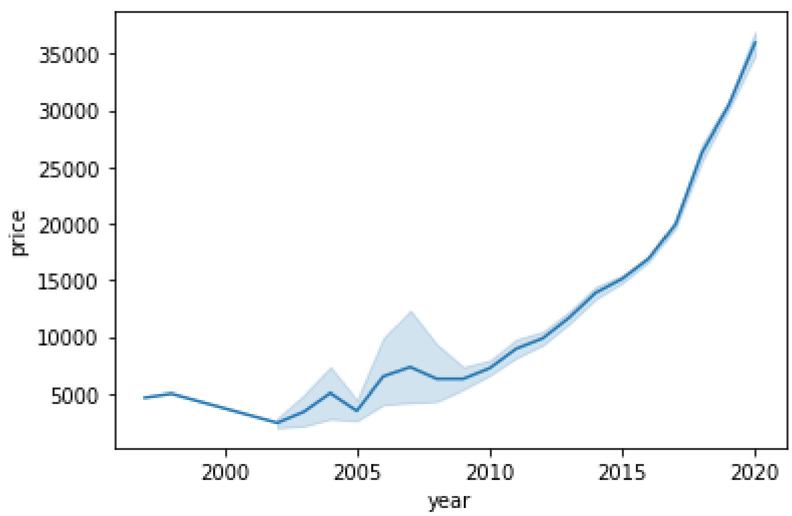
```
model           0
year            0
price           0
transmission    0
mileage         0
fuelType        0
tax             0
mpg             0
engineSize      0
dtype: int64
```

```
# use describe() to examine the data
df.describe()
```

	year	price	mileage	tax	mpg	engineSiz
count	10668.000000	10668.000000	10668.000000	10668.000000	10668.000000	10668.0000(
mean	2017.100675	22896.685039	24827.244001	126.011436	50.770022	1.9307(
std	2.167494	11714.841888	23505.257205	67.170294	12.949782	0.6029!
min	1997.000000	1490.000000	1.000000	0.000000	18.900000	0.0000(
25%	2016.000000	15130.750000	5968.750000	125.000000	40.900000	1.5000(
50%	2017.000000	20200.000000	19000.000000	145.000000	49.600000	2.0000(
75%	2019.000000	27990.000000	36464.500000	145.000000	58.900000	2.0000(
max	2020.000000	145000.000000	323000.000000	580.000000	188.300000	6.3000(

```
# using seaborn, craete a lineplot() with year on the x axis and price on the y axis
sb.lineplot(x=df['year'], y=df['price'])
```

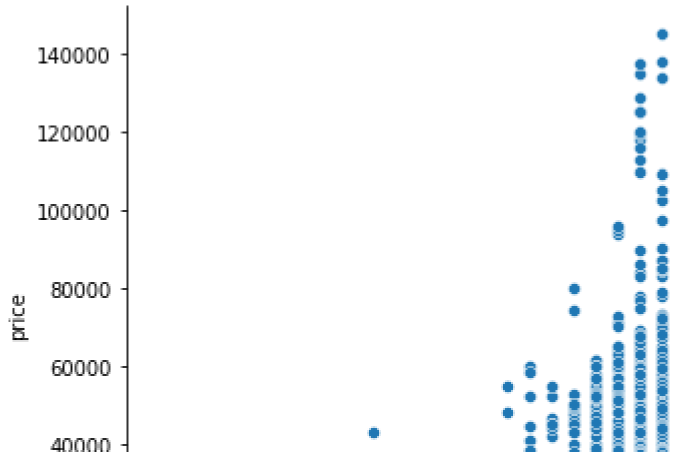
<matplotlib.axes._subplots.AxesSubplot at 0x7f4d7c622bd0>




```
# create another plot exploring the data
# choose columns and plot type

sb.relplot(x='year', y='price', data=df)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f4d7c54c1d0>
```



Step 4 Prepare Data

You can use the code below for this step.

```
# set up X and y

X=df.drop(columns=['price'],axis=1)
y=df['price']


import numpy as np
from sklearn.preprocessing import MinMaxScaler, LabelBinarizer
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split


X_train,X_test,y_train,y_test=train_test_split(X, y, test_size=0.2)

# scale the numeric data
col_list = ['year', 'mileage', 'tax', 'mpg', 'engineSize']
scaler = MinMaxScaler()
train_numeric = scaler.fit_transform(X_train[col_list])
test_numeric = scaler.transform(X_test[col_list])

# one-hot encode the categorical data for model, transmission, and fuelType
# model
zipBinarizer = LabelBinarizer().fit(df['model'])
train_model = zipBinarizer.transform(X_train['model'])
test_model = zipBinarizer.transform(X_test['model'])
# transmission
zipBinarizer = LabelBinarizer().fit(df['transmission'])
train_transmission = zipBinarizer.transform(X_train['transmission'])
test_transmission = zipBinarizer.transform(X_test['transmission'])
# fuelType
zipBinarizer = LabelBinarizer().fit(df['fuelType'])
train_fuelType = zipBinarizer.transform(X_train['fuelType'])
```

```
test_fuelType = zipBinarizer.transform(X_test['fuelType'])

# concatenate
X_train_input = np.hstack([train_numeric, train_model, train_transmission, train_fuelT
X_test_input = np.hstack([test_numeric, test_model, test_transmission, test_fuelType])

print(X_train_input[:3])
```

```
[[0.82608696 0.08549562 0.34482759 0.16646989 0.31746032 0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         1.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         1.         0.         0.         1.         0.
  0.        ]
 [0.82608696 0.16956399 0.25       0.22195986 0.31746032 0.
  0.         0.         0.         1.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         1.         0.         1.         0.
  0.        ]
 [0.86956522 0.06832219 0.34482759 0.12691854 0.31746032 1.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         1.         0.         0.         0.
  1.        ]]
```

Step 5 Linear regression

Run linear regression in sklearn.

```
# train the algorithm
from sklearn.linear_model import LinearRegression

linreg = LinearRegression()
linreg.fit(X_train_input, y_train)
```

```
LinearRegression()
```

```
# make predictions
y_pred = linreg.predict(X_test_input)
```

```
# evaluation on the test data using mse, mae, and r2_score
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

```
print('MSE: ', mean_squared_error(y_test, y_pred))
print('MAE: ', mean_absolute_error(y_test, y_pred))
print('r2: ', r2_score(y_test, y_pred))
```

```
MSE:  14011962.625299402
MAE:  2547.2941618731647
r2:  0.8872992801931721
```

```
# display the first 5 predictions
print(y_pred[:5])
```

```
[30522.97956788 12908.02941015 10678.90954458 27933.18126284
 19806.44953011]
```

```
# display the first 5 actual values
print(y_test[:5])
```

```
6051    31490
9284    12895
3562    11498
2780    25636
7542    31888
Name: price, dtype: int64
```

Regression in Keras

```
# build a sequential model
# choose the architecture

from tensorflow import keras
from tensorflow.keras import layers

model = keras.Sequential([
                          layers.Dense(500, activation='relu'),
                          layers.Dense(250, activation='relu'),
                          layers.Dense(64, activation='relu'),
                          layers.Dense(1)
])
```

```
# compile the model
model.compile(optimizer="rmsprop", loss="mean_squared_error", metrics=["mse","mae"])
```

```
# train the model
```

```
model.fit(X_train_input, y_train, epochs=100, batch_size=128)
```

```
67/67 [==============================] - 0s 6ms/step - loss: 7886041.0000 - mse:
Epoch 73/100
67/67 [==============================] - 0s 7ms/step - loss: 7824679.5000 - mse:
Epoch 74/100
67/67 [==============================] - 0s 7ms/step - loss: 7806488.0000 - mse:
Epoch 75/100
67/67 [==============================] - 0s 7ms/step - loss: 7721514.0000 - mse:
Epoch 76/100
67/67 [==============================] - 0s 7ms/step - loss: 7815334.5000 - mse:
Epoch 77/100
67/67 [==============================] - 1s 8ms/step - loss: 7757557.0000 - mse:
Epoch 78/100
67/67 [==============================] - 0s 7ms/step - loss: 7651753.0000 - mse:
Epoch 79/100
67/67 [==============================] - 1s 8ms/step - loss: 7727640.5000 - mse:
Epoch 80/100
67/67 [==============================] - 0s 7ms/step - loss: 7652880.0000 - mse:
Epoch 81/100
67/67 [==============================] - 0s 7ms/step - loss: 7681419.0000 - mse:
Epoch 82/100
67/67 [==============================] - 0s 7ms/step - loss: 7625214.5000 - mse:
Epoch 83/100
67/67 [==============================] - 0s 7ms/step - loss: 7654751.0000 - mse:
Epoch 84/100
67/67 [==============================] - 0s 7ms/step - loss: 7636537.0000 - mse:
Epoch 85/100
67/67 [==============================] - 1s 8ms/step - loss: 7546373.5000 - mse:
Epoch 86/100
67/67 [==============================] - 1s 7ms/step - loss: 7482979.0000 - mse:
Epoch 87/100
67/67 [==============================] - 1s 7ms/step - loss: 7487511.0000 - mse:
Epoch 88/100
67/67 [==============================] - 0s 7ms/step - loss: 7461997.5000 - mse:
Epoch 89/100
67/67 [==============================] - 1s 8ms/step - loss: 7457017.5000 - mse:
Epoch 90/100
67/67 [==============================] - 1s 7ms/step - loss: 7457679.5000 - mse:
Epoch 91/100
67/67 [==============================] - 1s 8ms/step - loss: 7422442.0000 - mse:
Epoch 92/100
67/67 [==============================] - 0s 7ms/step - loss: 7422161.0000 - mse:
Epoch 93/100
67/67 [==============================] - 0s 7ms/step - loss: 7354672.5000 - mse:
Epoch 94/100
67/67 [==============================] - 0s 7ms/step - loss: 7416666.0000 - mse:
Epoch 95/100
67/67 [==============================] - 1s 8ms/step - loss: 7381704.0000 - mse:
Epoch 96/100
67/67 [==============================] - 0s 7ms/step - loss: 7360501.5000 - mse:
Epoch 97/100
67/67 [==============================] - 1s 8ms/step - loss: 7309826.0000 - mse:
Epoch 98/100
67/67 [==============================] - 0s 7ms/step - loss: 7253979.5000 - mse:
Epoch 99/100
```

```
67/67 [==============================] - 0s 7ms/step - loss: 7296590.0000 - mse:
Epoch 100/100
67/67 [==============================] - 0s 7ms/step - loss: 7305990.5000 - mse:
<keras.callbacks.History at 0x7f4d0b945590>
```

```
# output test mse score, test mae score

loss, test_mse, test_mae = model.evaluate(X_test_input, y_test)
print('MSE:', test_mse)
print('MAE:', test_mae)
```

```
67/67 [==============================] - 0s 2ms/step - loss: 6042085.5000 - mse:
MSE: 6042085.5
MAE: 1705.4005126953125
```

Step 7 Commentary

Answer the following questions:

a. Compare metrics from sklearn and Keras.

b. Explore the data a bit more to speculate on why you achieved the results you got.

c. Describe all the architectures/hyperparameters you tried and the results. What do you conclude?

a.

Sklearn:

- MSE: 14011962.625299402
- MAE: 2547.2941618731647
- r2: 0.8872992801931721

Keras:

- MSE: 6042085.5
- MAE: 1705.4005126953125

Keras did significantly better than sklearn

b. I think my results were not that great. I think we are using too many predictors which cause too much noise for the algorithms to work with efficiently. Removing unneeded predictors could possibly improve the results. Also, the various predictors have a wide range so scaling or normalizing the data could also prove effective.

c. One of the first models I tried was 1 layer with 5 nodes with relu as the activation function. I used rmsprop as the optimizer, and mean_squared_error as the loss function. I got a mse score of 675202112.0000 and a mae score of 23048.5840. Which, of course, is extremely poor.

Next, I changed the model architecture to 3 layers with 64 nodes in layers 1 and 2 and 1 node in the last layer. The results were much better at mseL 9855431.0000 and mae: 2057.0847

The best results I got was with 4 layers of 500, 250, 64, 1 and 100 epochs. MSE: 6042085.5 MAE: 1705.4005126953125

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