project-maha

May 25, 2024

1 Car Price Predication

2 1. Explore the data

```
[5]: df.shape
[5]: (205, 26)
[6]: df.head()
[6]:
        car_ID
                 symboling
                                               CarName fueltype aspiration doornumber
                          3
              1
                                   alfa-romero giulia
                                                              gas
                                                                          std
     1
              2
                          3
                                   alfa-romero stelvio
                                                              gas
                                                                          std
                                                                                      two
     2
              3
                          1
                             alfa-romero Quadrifoglio
                                                                          std
                                                              gas
                                                                                      two
     3
              4
                          2
                                           audi 100 ls
                                                              gas
                                                                          std
                                                                                     four
              5
                          2
                                            audi 1001s
                                                                          std
                                                                                     four
                                                              gas
             carbody drivewheel enginelocation
                                                   wheelbase
                                                                  enginesize
        convertible
                                                        88.6
     0
                             rwd
                                           front
                                                                          130
                                                        88.6
                                                                          130
     1
        convertible
                             rwd
                                           front
     2
          hatchback
                             rwd
                                           front
                                                        94.5
                                                                          152
                                                        99.8
     3
               sedan
                             fwd
                                           front
                                                                          109
               sedan
                             4wd
                                           front
                                                        99.4
                                                                          136
        fuelsystem boreratio
                                 stroke compressionratio horsepower
                                                                         peakrpm citympg
     0
               mpfi
                           3.47
                                    2.68
                                                       9.0
                                                                   111
                                                                            5000
                                                                                       21
                                                       9.0
     1
               mpfi
                           3.47
                                   2.68
                                                                   111
                                                                            5000
                                                                                       21
```

```
2
                    2.68
                             3.47
                                               9.0
                                                           154
                                                                   5000
                                                                              19
         mpfi
3
         mpfi
                    3.19
                             3.40
                                              10.0
                                                           102
                                                                   5500
                                                                              24
4
                    3.19
                             3.40
                                               8.0
                                                           115
                                                                   5500
                                                                              18
         mpfi
   highwaympg
                 price
0
               13495.0
           27
           27 16500.0
1
2
           26
               16500.0
3
           30 13950.0
4
           22 17450.0
[5 rows x 26 columns]
```

```
[7]: df.columns
```

```
[7]: Index(['car_ID', 'symboling', 'CarName', 'fueltype', 'aspiration',
            'doornumber', 'carbody', 'drivewheel', 'enginelocation', 'wheelbase',
            'carlength', 'carwidth', 'carheight', 'curbweight', 'enginetype',
            'cylindernumber', 'enginesize', 'fuelsystem', 'boreratio', 'stroke',
            'compressionratio', 'horsepower', 'peakrpm', 'citympg', 'highwaympg',
            'price'],
           dtype='object')
```

[8]: df.info()

#	Column	Non-Null Count	Dtype
0	car_ID	205 non-null	int64
1	symboling	205 non-null	int64
2	CarName	205 non-null	object
3	fueltype	205 non-null	object
4	aspiration	205 non-null	object
5	doornumber	205 non-null	object
6	carbody	205 non-null	object
7	drivewheel	205 non-null	object
8	enginelocation	205 non-null	object
9	wheelbase	205 non-null	float64
10	carlength	205 non-null	float64
11	carwidth	205 non-null	float64
12	carheight	205 non-null	float64
13	curbweight	205 non-null	int64
14	enginetype	205 non-null	object
15	cylindernumber	205 non-null	object
16	enginesize	205 non-null	int64

```
17 fuelsystem
                       205 non-null
                                       object
 18 boreratio
                       205 non-null
                                       float64
 19
    stroke
                       205 non-null
                                       float64
 20
    compressionratio 205 non-null
                                       float64
 21
    horsepower
                       205 non-null
                                        int64
 22
                       205 non-null
    peakrpm
                                        int64
 23
    citympg
                       205 non-null
                                        int64
 24 highwaympg
                       205 non-null
                                        int64
                       205 non-null
                                       float64
 25 price
dtypes: float64(8), int64(8), object(10)
```

memory usage: 41.8+ KB

[9]: df['CarName'].unique()

```
[9]: array(['alfa-romero giulia', 'alfa-romero stelvio',
            'alfa-romero Quadrifoglio', 'audi 100 ls', 'audi 100ls',
            'audi fox', 'audi 5000', 'audi 4000', 'audi 5000s (diesel)',
            'bmw 320i', 'bmw x1', 'bmw x3', 'bmw z4', 'bmw x4', 'bmw x5',
            'chevrolet impala', 'chevrolet monte carlo', 'chevrolet vega 2300',
            'dodge rampage', 'dodge challenger se', 'dodge d200',
            'dodge monaco (sw)', 'dodge colt hardtop', 'dodge colt (sw)',
            'dodge coronet custom', 'dodge dart custom',
            'dodge coronet custom (sw)', 'honda civic', 'honda civic cvcc',
            'honda accord cvcc', 'honda accord lx', 'honda civic 1500 gl',
            'honda accord', 'honda civic 1300', 'honda prelude',
            'honda civic (auto)', 'isuzu MU-X', 'isuzu D-Max',
            'isuzu D-Max V-Cross', 'jaguar xj', 'jaguar xf', 'jaguar xk',
            'maxda rx3', 'maxda glc deluxe', 'mazda rx2 coupe', 'mazda rx-4',
            'mazda glc deluxe', 'mazda 626', 'mazda glc', 'mazda rx-7 gs',
            'mazda glc 4', 'mazda glc custom l', 'mazda glc custom',
            'buick electra 225 custom', 'buick century luxus (sw)',
            'buick century', 'buick skyhawk', 'buick opel isuzu deluxe',
            'buick skylark', 'buick century special',
            'buick regal sport coupe (turbo)', 'mercury cougar',
            'mitsubishi mirage', 'mitsubishi lancer', 'mitsubishi outlander',
            'mitsubishi g4', 'mitsubishi mirage g4', 'mitsubishi montero',
            'mitsubishi pajero', 'Nissan versa', 'nissan gt-r', 'nissan rogue',
            'nissan latio', 'nissan titan', 'nissan leaf', 'nissan juke',
            'nissan note', 'nissan clipper', 'nissan nv200', 'nissan dayz',
            'nissan fuga', 'nissan otti', 'nissan teana', 'nissan kicks',
            'peugeot 504', 'peugeot 304', 'peugeot 504 (sw)', 'peugeot 604sl',
            'peugeot 505s turbo diesel', 'plymouth fury iii',
            'plymouth cricket', 'plymouth satellite custom (sw)',
            'plymouth fury gran sedan', 'plymouth valiant', 'plymouth duster',
            'porsche macan', 'porcshce panamera', 'porsche cayenne',
            'porsche boxter', 'renault 12tl', 'renault 5 gtl', 'saab 99e',
            'saab 99le', 'saab 99gle', 'subaru', 'subaru dl', 'subaru brz',
```

```
'subaru baja', 'subaru r1', 'subaru r2', 'subaru trezia',
             'subaru tribeca', 'toyota corona mark ii', 'toyota corona',
             'toyota corolla 1200', 'toyota corona hardtop',
             'toyota corolla 1600 (sw)', 'toyota carina', 'toyota mark ii',
             'toyota corolla', 'toyota corolla liftback',
             'toyota celica gt liftback', 'toyota corolla tercel',
             'toyota corona liftback', 'toyota starlet', 'toyota tercel',
             'toyota cressida', 'toyota celica gt', 'toyouta tercel',
             'vokswagen rabbit', 'volkswagen 1131 deluxe sedan',
             'volkswagen model 111', 'volkswagen type 3', 'volkswagen 411 (sw)',
             'volkswagen super beetle', 'volkswagen dasher', 'vw dasher',
             'vw rabbit', 'volkswagen rabbit', 'volkswagen rabbit custom',
             'volvo 145e (sw)', 'volvo 144ea', 'volvo 244dl', 'volvo 245',
             'volvo 264gl', 'volvo diesel', 'volvo 246'], dtype=object)
[10]: df['fueltype'].unique()
[10]: array(['gas', 'diesel'], dtype=object)
[11]: df['aspiration'].unique()
[11]: array(['std', 'turbo'], dtype=object)
[12]: df['doornumber'].unique()
[12]: array(['two', 'four'], dtype=object)
[13]: #replace the text values with numbers
      df['doornumber'].replace('two',2,inplace=True)
      df['doornumber'].replace('four',4,inplace=True)
      df['doornumber'].unique()
[13]: array([2, 4], dtype=int64)
[14]: df['carbody'].unique()
      df['drivewheel'].unique()
      df['enginelocation'].unique()
      df['wheelbase'].unique()
      df['carlength'].unique()
      df['carwidth'].unique()
      df['carheight'].unique()
[14]: array([48.8, 52.4, 54.3, 53.1, 55.7, 55.9, 52., 53.7, 56.3, 53.2, 50.8,
             50.6, 59.8, 50.2, 52.6, 54.5, 58.3, 53.3, 54.1, 51., 53.5, 51.4,
             52.8, 47.8, 49.6, 55.5, 54.4, 56.5, 58.7, 54.9, 56.7, 55.4, 54.8,
             49.4, 51.6, 54.7, 55.1, 56.1, 49.7, 56., 50.5, 55.2, 52.5, 53.,
             59.1, 53.9, 55.6, 56.2, 57.5])
```

```
[15]: def unique(x):
          return df[x].unique()
[16]: unique('curbweight')
      unique('cylindernumber')
[16]: array(['four', 'six', 'five', 'three', 'twelve', 'two', 'eight'],
            dtype=object)
[17]: df['cylindernumber'].replace('four',4,inplace=True)
      df['cylindernumber'].replace('six',6,inplace=True)
      df['cylindernumber'].replace('five',5,inplace=True)
      df['cylindernumber'].replace('three',3,inplace=True)
      df['cylindernumber'].replace('twelve',12,inplace=True)
      df['cylindernumber'].replace('two',2,inplace=True)
      df['cylindernumber'].replace('eight',8,inplace=True)
      df['cylindernumber'].unique()
[17]: array([ 4, 6, 5, 3, 12, 2, 8], dtype=int64)
[18]: unique('enginesize')
      unique('fuelsystem')
      unique('boreratio')
      unique('stroke')
      unique('compressionratio')
      unique('horsepower')
      unique('peakrpm')
      unique('citympg')
      unique('highwaympg')
      unique('price')
[18]: array([13495.
                      , 16500.
                                  , 13950.
                                             , 17450.
                                                        , 15250.
                                                                    , 17710.
             18920.
                      , 23875.
                                  , 17859.167, 16430.
                                                        , 16925.
                                                                    , 20970.
             21105.
                      , 24565.
                                   30760.
                                             , 41315.
                                                        , 36880.
                                                                      5151.
              6295.
                      , 6575.
                                    5572.
                                                6377.
                                                           7957.
                                                                      6229.
                        7609.
              6692.
                                    8558.
                                                8921.
                                                        , 12964.
                                                                      6479.
              6855.
                       5399.
                                    6529.
                                               7129.
                                                                      7895.
                                                          7295.
              9095.
                        8845.
                                  , 10295.
                                             , 12945.
                                                        , 10345.
                                                                      6785.
                      , 11048.
              8916.5
                                  , 32250.
                                             , 35550.
                                                        , 36000.
                                                                      5195.
              6095.
                      , 6795.
                                    6695.
                                              7395.
                                                        . 10945.
                                                                    , 11845.
             13645.
                      , 15645.
                                    8495.
                                             , 10595.
                                                        , 10245.
                                                                    , 10795.
                                  , 18344.
                                                                    , 28176.
             11245.
                      , 18280.
                                             , 25552.
                                                        . 28248.
             31600.
                      , 34184.
                                  , 35056.
                                             , 40960.
                                                        , 45400.
                                                                    , 16503.
                      . 6189.
              5389.
                                    6669.
                                             . 7689.
                                                        . 9959.
                                                                      8499.
             12629.
                      , 14869.
                                  , 14489.
                                               6989.
                                                        , 8189.
                                                                      9279.
              5499.
                      , 7099.
                                    6649.
                                                6849.
                                                           7349.
                                                                      7299.
              7799.
                      , 7499.
                                    7999.
                                               8249.
                                                           8949.
                                                                      9549.
```

```
13499.
          , 14399.
                      , 17199.
                                   , 19699.
                                               , 18399.
                                                            , 11900.
13200.
          , 12440.
                      , 13860.
                                   , 15580.
                                               , 16900.
                                                              16695.
17075.
          , 16630.
                      , 17950.
                                   , 18150.
                                               , 12764.
                                                              22018.
          , 34028.
32528.
                      , 37028.
                                   , 31400.5
                                                  9295.
                                                               9895.
11850.
          , 12170.
                      , 15040.
                                    15510.
                                                 18620.
                                                               5118.
7053.
             7603.
                         7126.
                                      7775.
                                                  9960.
                                                               9233.
                        10198.
                                      8013.
11259.
             7463.
                                               , 11694.
                                                               5348.
6338.
             6488.
                         6918.
                                      7898.
                                                  8778.
                                                               6938.
             7788.
7198.
                         7738.
                                      8358.
                                                  9258.
                                                               8058.
8238.
             9298.
                         9538.
                                      8449.
                                                  9639.
                                                               9989.
11199.
          , 11549.
                      , 17669.
                                      8948.
                                               , 10698.
                                                              9988.
10898.
          , 11248.
                      , 16558.
                                    15998.
                                               , 15690.
                                                             15750.
7975.
             7995.
                         8195.
                                      9495.
                                                  9995.
                                                             11595.
9980.
          , 13295.
                      , 13845.
                                   , 12290.
                                               , 12940.
                                                             13415.
                                                            , 19045.
15985.
          , 16515.
                      , 18420.
                                   , 18950.
                                               , 16845.
          , 22470.
                                  ])
21485.
                        22625.
```

3 2. Data Preprocessing.

[19]: df.info()

#	Column	Non-Null Count	Dtype
0	car_ID	205 non-null	int64
1	symboling	205 non-null	int64
2	CarName	205 non-null	object
3	fueltype	205 non-null	object
4	aspiration	205 non-null	object
5	doornumber	205 non-null	int64
6	carbody	205 non-null	object
7	drivewheel	205 non-null	object
8	enginelocation	205 non-null	object
9	wheelbase	205 non-null	float64
10	carlength	205 non-null	float64
11	carwidth	205 non-null	float64
12	carheight	205 non-null	float64
13	curbweight	205 non-null	int64
14	enginetype	205 non-null	object
15	cylindernumber	205 non-null	int64
16	enginesize	205 non-null	int64
17	fuelsystem	205 non-null	object
18	boreratio	205 non-null	float64
19	stroke	205 non-null	float64

```
float64
      20
          compressionratio 205 non-null
      21 horsepower
                             205 non-null
                                              int64
      22
         peakrpm
                             205 non-null
                                              int64
      23 citympg
                             205 non-null
                                              int64
      24 highwaympg
                             205 non-null
                                              int64
      25 price
                             205 non-null
                                             float64
     dtypes: float64(8), int64(10), object(8)
     memory usage: 41.8+ KB
[20]: # check for null values
      df.isna().sum()
[20]: car_ID
                          0
      symboling
                          0
      CarName
                          0
                          0
      fueltype
      aspiration
                          0
                          0
      doornumber
                          0
      carbody
      drivewheel
                          0
      enginelocation
                          0
      wheelbase
                          0
      carlength
                          0
      carwidth
                          0
      carheight
                          0
      curbweight
                          0
      enginetype
                          0
      cylindernumber
                          0
      enginesize
                          0
      fuelsystem
                          0
      boreratio
                          0
      stroke
                          0
      compressionratio
                          0
      horsepower
                          0
      peakrpm
                          0
                          0
      citympg
                          0
      highwaympg
      price
                          0
      dtype: int64
[21]: # check for duplicates
      df.duplicated().sum()
[21]: 0
```

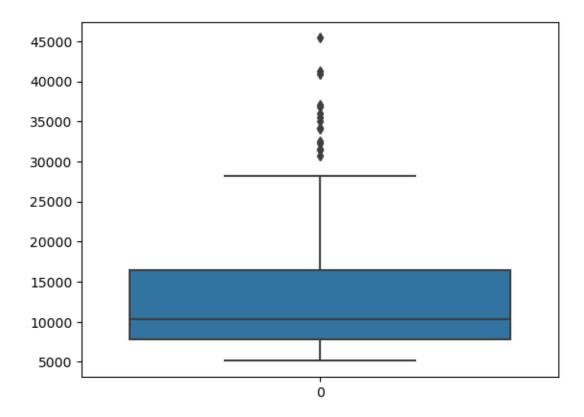
[22]: df.columns

```
[22]: Index(['car_ID', 'symboling', 'CarName', 'fueltype', 'aspiration',
              'doornumber', 'carbody', 'drivewheel', 'enginelocation', 'wheelbase',
              'carlength', 'carwidth', 'carheight', 'curbweight', 'enginetype',
              'cylindernumber', 'enginesize', 'fuelsystem', 'boreratio', 'stroke',
              'compressionratio', 'horsepower', 'peakrpm', 'citympg', 'highwaympg',
              'price'],
            dtype='object')
[23]: # statistical analysis
      df.describe()
[23]:
                  car ID
                           symboling
                                       doornumber
                                                     wheelbase
                                                                  carlength
                                                                                carwidth
             205.000000
                          205.000000
                                       205.000000
                                                                 205.000000
                                                    205.000000
                                                                             205.000000
      count
                                                                 174.049268
      mean
             103.000000
                            0.834146
                                         3.121951
                                                     98.756585
                                                                               65.907805
                                                                  12.337289
      std
              59.322565
                            1.245307
                                         0.994966
                                                      6.021776
                                                                                2.145204
      min
               1.000000
                           -2.000000
                                         2.000000
                                                     86.600000
                                                                 141.100000
                                                                               60.300000
      25%
              52.000000
                            0.000000
                                         2.000000
                                                     94.500000
                                                                 166.300000
                                                                               64.100000
      50%
             103.000000
                            1.000000
                                         4.000000
                                                     97.000000
                                                                 173.200000
                                                                               65.500000
      75%
              154.000000
                            2.000000
                                         4.000000
                                                    102.400000
                                                                 183.100000
                                                                               66.900000
             205.000000
                                         4.000000
                                                    120.900000
      max
                            3.000000
                                                                 208.100000
                                                                               72.300000
                                        cylindernumber
               carheight
                           curbweight
                                                         enginesize
                                                                       boreratio
                           205.000000
                                            205.000000
                                                         205.000000
                                                                      205.000000
      count
             205.000000
              53.724878
                          2555.565854
                                              4.380488
                                                         126.907317
                                                                        3.329756
      mean
      std
               2.443522
                           520.680204
                                               1.080854
                                                          41.642693
                                                                        0.270844
      min
              47.800000
                          1488.000000
                                              2.000000
                                                          61.000000
                                                                        2.540000
      25%
              52.000000
                          2145.000000
                                                          97.000000
                                               4.000000
                                                                        3.150000
      50%
              54.100000
                          2414.000000
                                              4.000000
                                                         120.000000
                                                                        3.310000
      75%
              55.500000
                          2935.000000
                                               4.000000
                                                         141.000000
                                                                        3.580000
      max
              59.800000
                          4066.000000
                                              12.000000
                                                         326.000000
                                                                        3.940000
                  stroke
                          compressionratio
                                             horsepower
                                                              peakrpm
                                                                           citympg
      count
             205.000000
                                 205.000000
                                              205.000000
                                                           205.000000
                                                                        205.000000
               3.255415
                                  10.142537
                                              104.117073
                                                          5125.121951
                                                                         25.219512
      mean
      std
               0.313597
                                   3.972040
                                              39.544167
                                                           476.985643
                                                                          6.542142
      min
               2.070000
                                   7.000000
                                               48.000000
                                                          4150.000000
                                                                         13.000000
      25%
                                   8.600000
                                               70.000000
                                                          4800.000000
                                                                         19.000000
               3.110000
      50%
               3.290000
                                   9.000000
                                               95.000000
                                                          5200.000000
                                                                         24.000000
      75%
               3.410000
                                   9.400000
                                              116.000000
                                                          5500.000000
                                                                         30.000000
               4.170000
                                  23.000000
                                              288.000000
                                                          6600.000000
                                                                         49.000000
      max
             highwaympg
                                  price
             205.000000
                            205.000000
      count
              30.751220
                          13276.710571
      mean
      std
               6.886443
                           7988.852332
      min
              16.000000
                           5118.000000
      25%
              25.000000
                           7788.000000
```

```
50% 30.000000 10295.000000 75% 34.000000 16503.000000 max 54.000000 45400.000000
```

```
[24]: #check for outliers
sns.boxplot(data=df['price'])
# ouliers are there, but not removing it.
```

[24]: <Axes: >



```
[25]: df.columns df.head()
```

```
[25]:
         car_ID symboling
                                              CarName fueltype aspiration \
      0
                         3
              1
                                  alfa-romero giulia
                                                           gas
                                                                       std
              2
      1
                         3
                                 alfa-romero stelvio
                                                                       std
                                                           gas
              3
      2
                         1 alfa-romero Quadrifoglio
                                                           gas
                                                                       std
      3
              4
                         2
                                          audi 100 ls
                                                           gas
                                                                       std
              5
                                           audi 1001s
                                                           gas
                                                                       std
         doornumber
                         carbody drivewheel enginelocation wheelbase ... \
      0
                  2 convertible
                                        rwd
                                                      front
                                                                  88.6 ...
```

1	2	convertible		rwd		front	88.	6		
2	2	hatchback		rwd		front	94.	5 		
3	4	sedan		fwd		front	99.	8		
4	4	sedan		4wd		front	99.	4		
	enginesize	fuelsystem	bore	ratio	stroke	compression	nratio	horse	power	\
0	130	mpfi		3.47	2.68		9.0		111	
1	130	mpfi		3.47	2.68		9.0		111	
2	152	mpfi		2.68	3.47		9.0		154	
3	109	mpfi		3.19	3.40		10.0		102	
4	136	mpfi		3.19	3.40		8.0		115	
	peakrpm cit	ympg highwa	ympg	pri	ce					
0	5000	21	27	13495	.0					
1	5000	21	27	16500	.0					
2	5000	19	26	16500	.0					
3	5500	24	30	13950	.0					
4	5500	18	22	17450	.0					

[5 rows x 26 columns]

[26]: #Encode the categorical datas from the dataset. For Ml Model generation

[27]: df.info()

#	Column	Non-Null Count	Dtype
0	car_ID	205 non-null	int64
1	symboling	205 non-null	int64
2	CarName	205 non-null	object
3	fueltype	205 non-null	object
4	aspiration	205 non-null	object
5	doornumber	205 non-null	int64
6	carbody	205 non-null	object
7	drivewheel	205 non-null	object
8	enginelocation	205 non-null	object
9	wheelbase	205 non-null	float64
10	carlength	205 non-null	float64
11	carwidth	205 non-null	float64
12	carheight	205 non-null	float64
13	curbweight	205 non-null	int64
14	enginetype	205 non-null	object
15	cylindernumber	205 non-null	int64
16	enginesize	205 non-null	int64

```
18 boreratio
                            205 non-null
                                            float64
                                            float64
      19 stroke
                            205 non-null
      20 compressionratio 205 non-null
                                            float64
      21 horsepower
                            205 non-null
                                            int64
      22 peakrpm
                            205 non-null
                                            int64
      23 citympg
                            205 non-null
                                            int64
                            205 non-null
                                            int64
      24 highwaympg
      25 price
                            205 non-null
                                            float64
     dtypes: float64(8), int64(10), object(8)
     memory usage: 41.8+ KB
[28]: #Encoding using Label Encoder
      from sklearn import preprocessing
      label=preprocessing.LabelEncoder()
[29]: label.fit(df.fueltype)
      df.fueltype=label.transform(df.fueltype)
[30]: label.fit(df.aspiration)
      df.aspiration=label.transform(df.aspiration)
[31]: label.fit(df.carbody)
      df.carbody=label.transform(df.carbody)
[32]: label.fit(df.drivewheel)
      df.drivewheel=label.transform(df.drivewheel)
[33]: label.fit(df.enginelocation)
      df.enginelocation=label.transform(df.enginelocation)
[34]: label.fit(df.enginetype)
      df.enginetype=label.transform(df.enginetype)
[35]: label.fit(df.fuelsystem)
      df.fuelsystem=label.transform(df.fuelsystem)
[36]: df.head()
[36]:
        car ID symboling
                                             CarName fueltype aspiration \
      0
             1
                         3
                                  alfa-romero giulia
                                                             1
             2
                         3
      1
                                 alfa-romero stelvio
                                                             1
                                                                         0
                         1 alfa-romero Quadrifoglio
      2
             3
                                                             1
                                                                         0
      3
              4
                         2
                                         audi 100 ls
                                                             1
                                                                         0
             5
                         2
                                          audi 1001s
                                                             1
                                                                         0
        doornumber carbody drivewheel enginelocation wheelbase ... \
```

205 non-null

object

17 fuelsystem

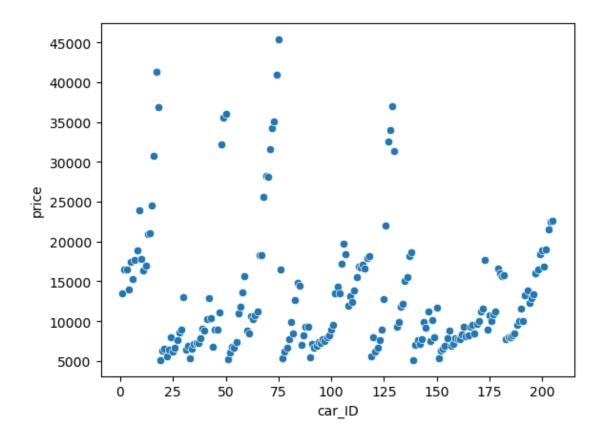
0		2	0		2		0	88.6			
1		2	0		2		0	88.6	•••		
2		2	2		2		0	94.5	•••		
3		4	3		1		0	99.8	•••		
4		4	3		0		0	99.4			
	onginogia	o fuola	1775±0m	horor	n+in	atroleo	compro	agionrotio	horgonor		\
	enginesiz		system	borer		stroke	compre	ssionratio	_		\
0	13	30	5		3.47	2.68		9.0	1	.11	
1	13	30	5		3.47	2.68		9.0	1	.11	
2	15	52	5		2.68	3.47		9.0	1	.54	
3	10	9	5		3.19	3.40		10.0	1	.02	
4	13	36	5		3.19	3.40		8.0	1	.15	
	_										
	${\tt peakrpm}$	citympg	highw	aympg	pr	ice					
0	5000	21		27	1349	5.0					
1	5000	21		27	1650	0.0					
2	5000	19		26	1650	0.0					
3	5500	24		30	1395	0.0					
4	5500	18		22	1745	0.0					

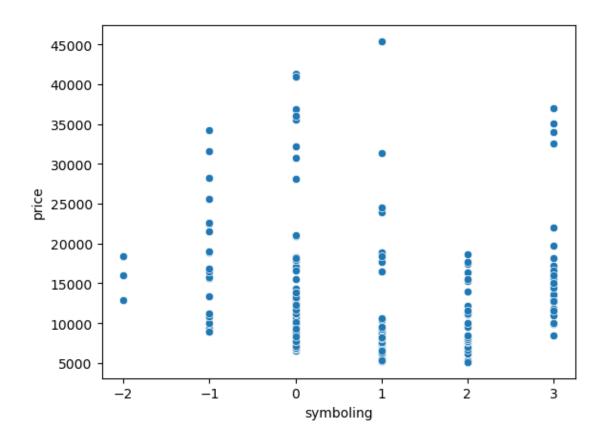
[5 rows x 26 columns]

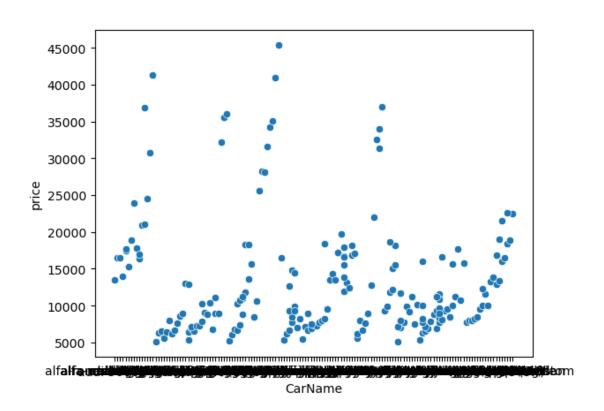
[37]: df.info()

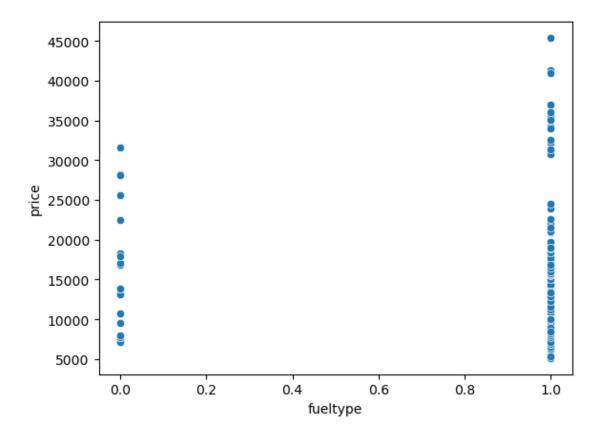
#	Column	Non-Null Count	Dtype
0	car_ID	205 non-null	int64
1	symboling	205 non-null	int64
2	CarName	205 non-null	object
3	fueltype	205 non-null	int32
4	aspiration	205 non-null	int32
5	doornumber	205 non-null	int64
6	carbody	205 non-null	int32
7	drivewheel	205 non-null	int32
8	enginelocation	205 non-null	int32
9	wheelbase	205 non-null	float64
10	carlength	205 non-null	float64
11	carwidth	205 non-null	float64
12	carheight	205 non-null	float64
13	curbweight	205 non-null	int64
14	enginetype	205 non-null	int32
15	cylindernumber	205 non-null	int64
16	enginesize	205 non-null	int64
17	fuelsystem	205 non-null	int32

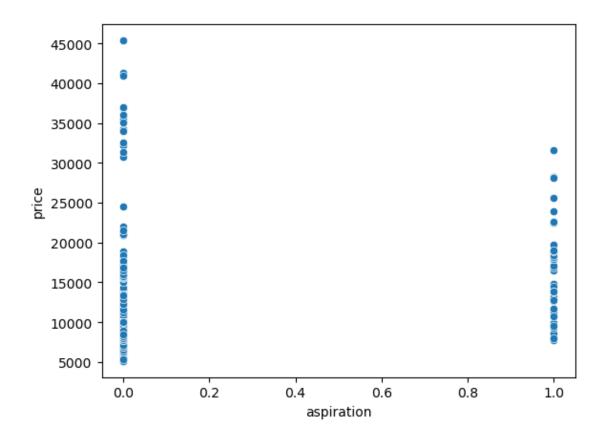
```
18 boreratio
                            205 non-null
                                            float64
      19 stroke
                            205 non-null
                                            float64
      20 compressionratio 205 non-null
                                            float64
      21 horsepower
                            205 non-null
                                            int64
      22 peakrpm
                            205 non-null
                                            int64
      23 citympg
                            205 non-null
                                            int64
      24 highwaympg
                            205 non-null
                                            int64
                            205 non-null
                                            float64
      25 price
     dtypes: float64(8), int32(7), int64(10), object(1)
     memory usage: 36.2+ KB
[38]: # check the correlation between 'price' and independent variables
[39]: df.columns
[39]: Index(['car_ID', 'symboling', 'CarName', 'fueltype', 'aspiration',
             'doornumber', 'carbody', 'drivewheel', 'enginelocation', 'wheelbase',
             'carlength', 'carwidth', 'carheight', 'curbweight', 'enginetype',
             'cylindernumber', 'enginesize', 'fuelsystem', 'boreratio', 'stroke',
             'compressionratio', 'horsepower', 'peakrpm', 'citympg', 'highwaympg',
             'price'],
            dtype='object')
[40]: | # Creating scatter plots for each numerical column against 'price'
      for col in df:
          sns.scatterplot(data=df, x=col, y='price')
          plt.show()
```

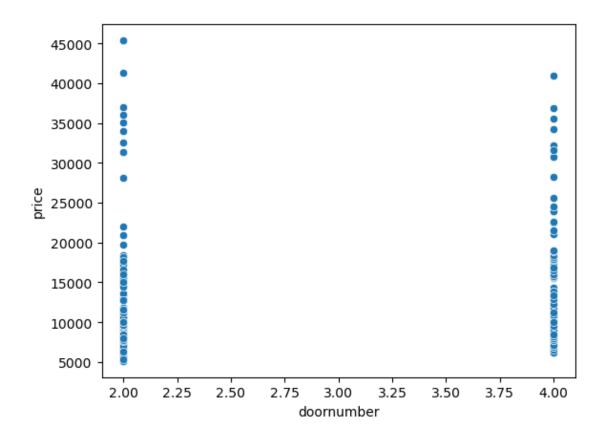


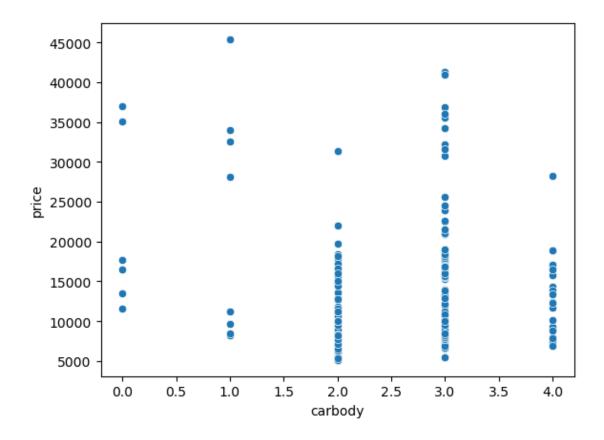


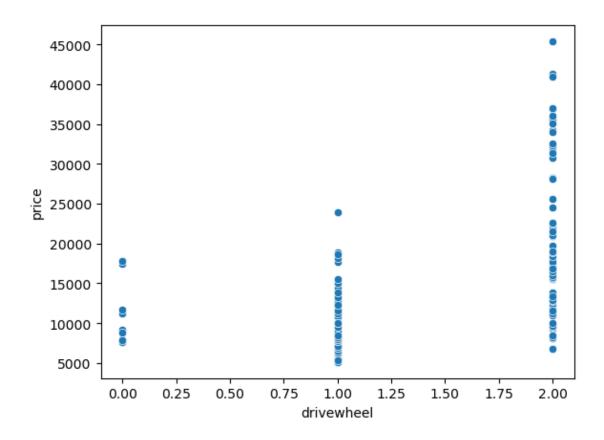


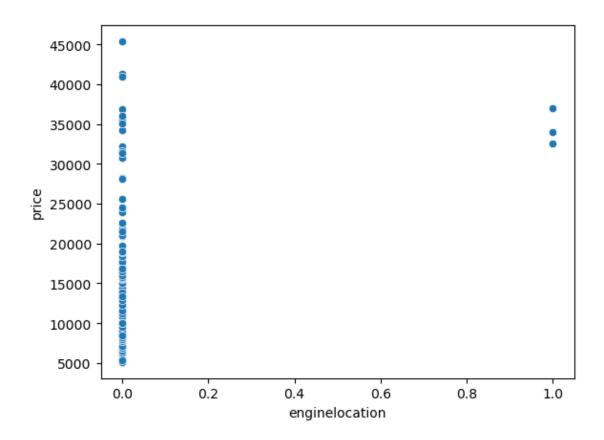


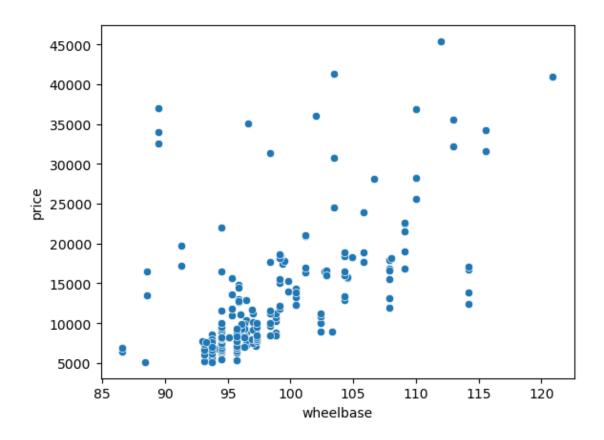


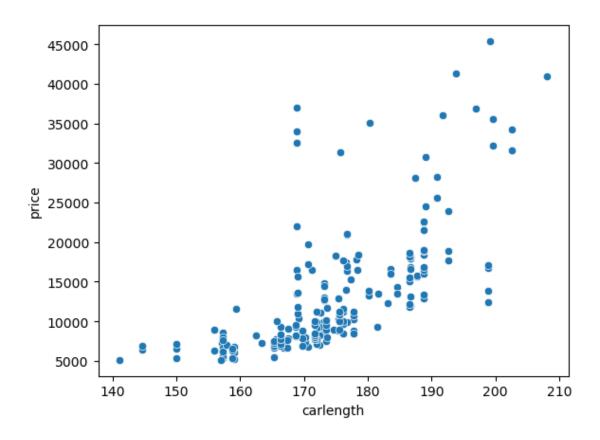


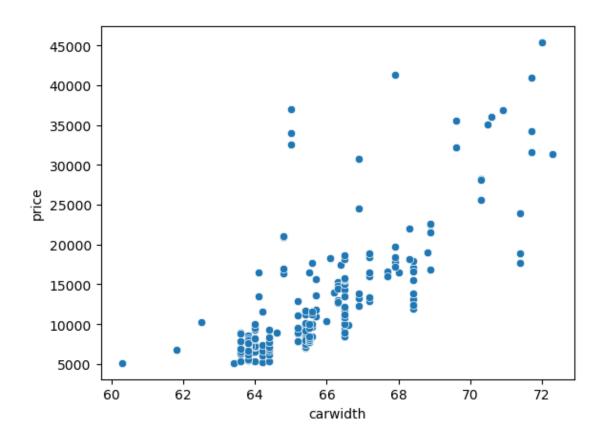


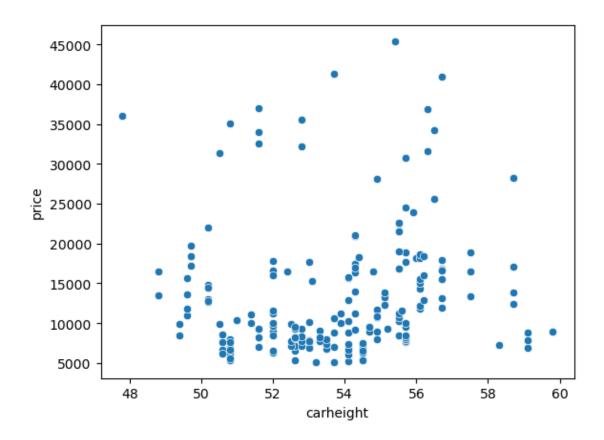


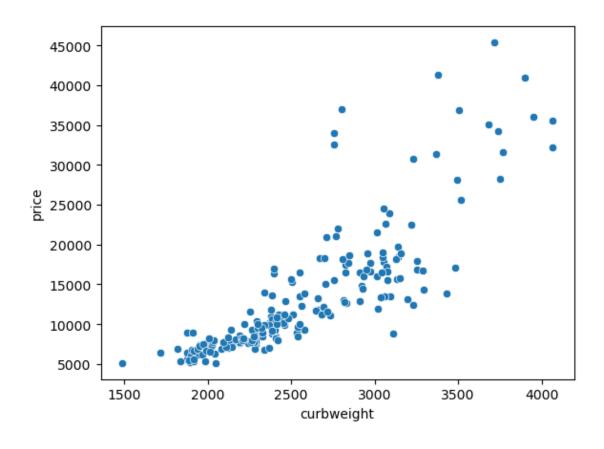


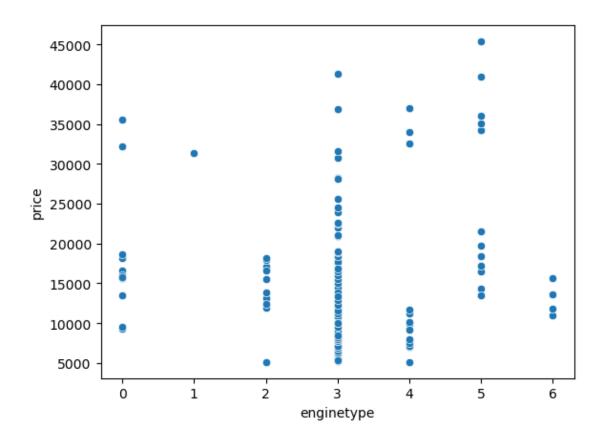


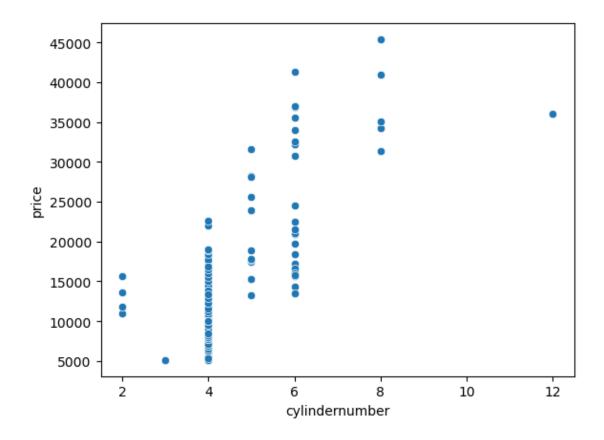


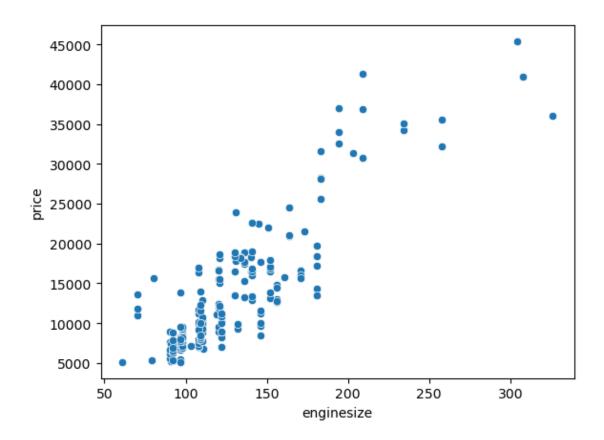


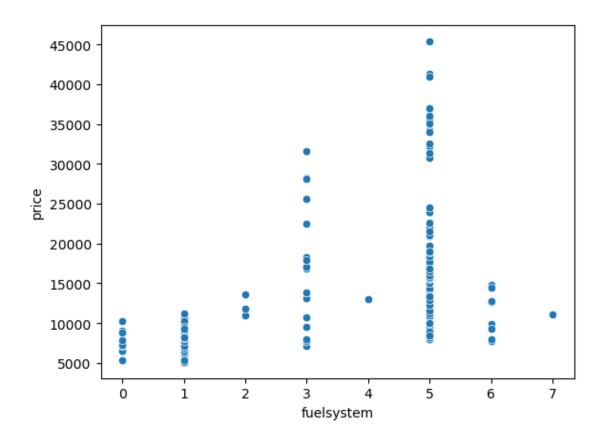


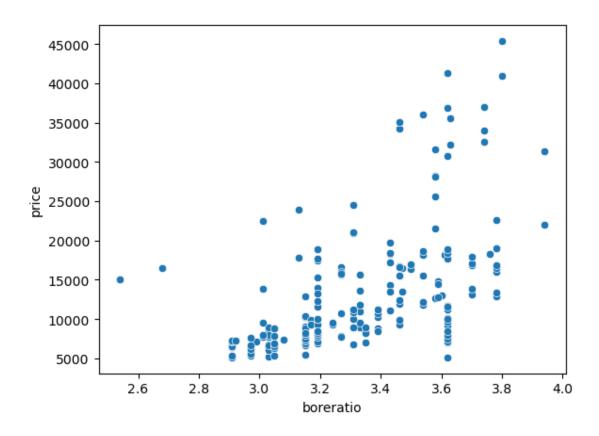


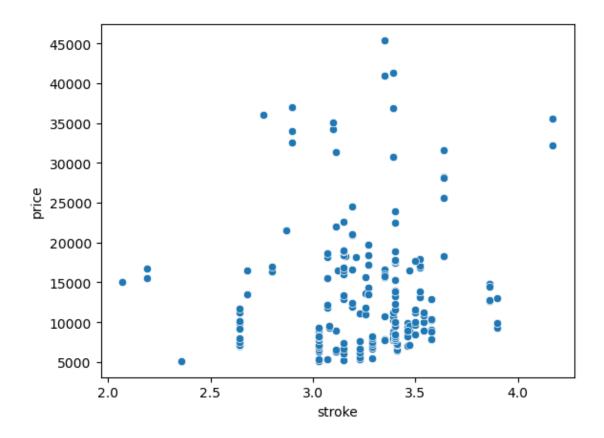


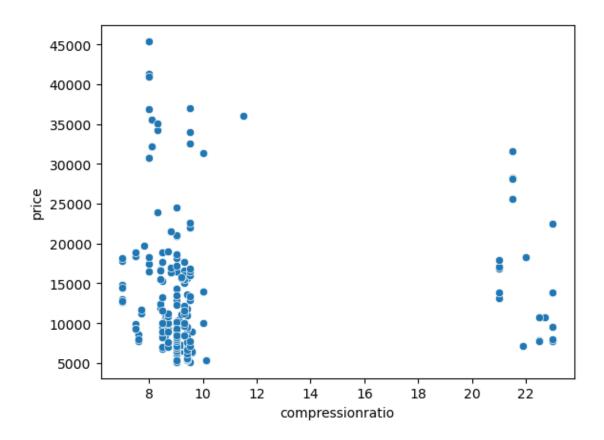


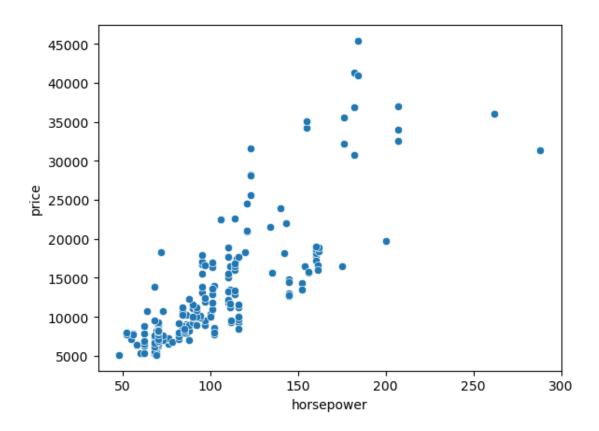


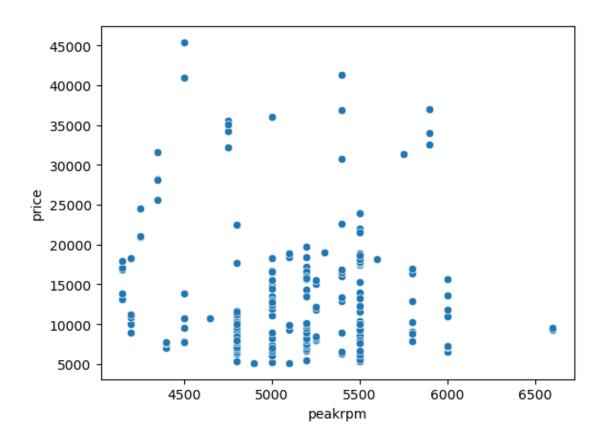


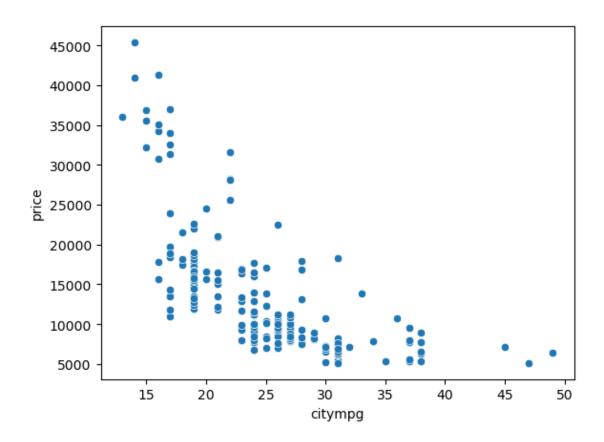


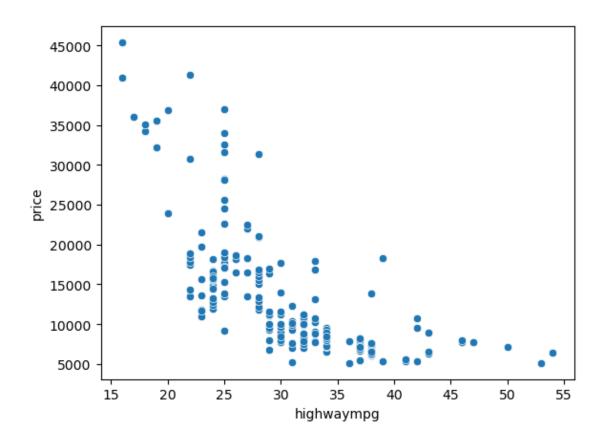


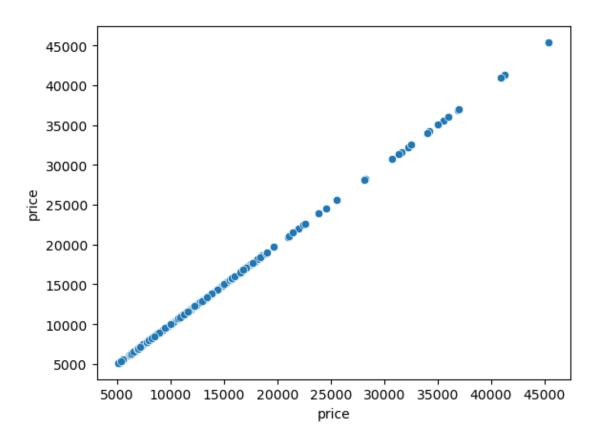












[41]: # plot a heatmap to show the correlation among numerical variables.

```
ValueError Traceback (most recent call last)

Cell In[43], line 2

1 # Create a correlation matrix between numerical columns

----> 2 correlation_matrix = df.corr()

4 plt.figure(figsize=(12, 10))

5 sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f',

columns

-----> linewidths=0.5)
```

```
File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:10704, in DataFrame.
 Gorr(self, method, min_periods, numeric_only)
 10702 cols = data.columns
  10703 idx = cols.copy()
> 10704 mat = data.to_numpy(dtype=float, na_value=np.nan, copy=False)
  10706 if method == "pearson":
            correl = libalgos.nancorr(mat, minp=min_periods)
File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:1889, in DataFrame.
 sto_numpy(self, dtype, copy, na_value)
   1887 if dtype is not None:
            dtype = np.dtype(dtype)
   1888
-> 1889 result = self._mgr.as_array(dtype=dtype, copy=copy, na_value=na_value)
   1890 if result.dtype is not dtype:
            result = np.array(result, dtype=dtype, copy=False)
   1891
File ~\anaconda3\Lib\site-packages\pandas\core\internals\managers.py:1656, in _
 →BlockManager.as_array(self, dtype, copy, na_value)
   1654
                arr.flags.writeable = False
   1655 else:
-> 1656 arr = self._interleave(dtype=dtype, na_value=na_value)
            # The underlying data was copied within _interleave, so no need
   1657
            # to further copy if copy=True or setting na_value
   1660 if na_value is lib.no_default:
File ~\anaconda3\Lib\site-packages\pandas\core\internals\managers.py:1715, in_
 →BlockManager._interleave(self, dtype, na_value)
            else:
   1713
   1714
                arr = blk.get_values(dtype)
-> 1715
           result[rl.indexer] = arr
            itemmask[rl.indexer] = 1
   1716
   1718 if not itemmask.all():
ValueError: could not convert string to float: 'alfa-romero giulia'
```

3.1 Observations from scatter plot and heatmap

The independent variables that affects the price of car are, 1. 'drivewheel' 2. 'wheelbase' 3. 'carlength' 4. 'carwidth' 5. 'curbweight' 6. 'cylindernumber' 7. 'enginesize' 8. 'fuelsystem' 9. 'boreratio' 10. 'horsepower' 11. 'citympg' (negative correlation) 12. 'highwaympg' (negative correlation)

```
[45]: independent_data_for_model=df[columns_to_sort]
      independent_data_for_model.head()
[45]:
         drivewheel wheelbase
                                                        curbweight cylindernumber
                                  carlength carwidth
                   2
                            88.6
                                       168.8
                                                   64.1
                                                                2548
      0
                                                                                    4
                   2
      1
                            88.6
                                       168.8
                                                   64.1
                                                                2548
                                                                                    4
      2
                   2
                            94.5
                                       171.2
                                                   65.5
                                                                2823
                                                                                    6
      3
                   1
                            99.8
                                       176.6
                                                   66.2
                                                                2337
                                                                                    4
      4
                   0
                            99.4
                                       176.6
                                                   66.4
                                                                                    5
                                                                2824
         enginesize
                      fuelsystem
                                   boreratio horsepower
                                                            citympg
                                                                      highwaympg
      0
                 130
                                5
                                         3.47
                                                       111
                                                                  21
                                                                               27
                 130
                                5
                                                                  21
                                                                               27
      1
                                         3.47
                                                       111
                                5
      2
                 152
                                         2.68
                                                       154
                                                                  19
                                                                               26
      3
                 109
                                5
                                         3.19
                                                       102
                                                                  24
                                                                               30
      4
                 136
                                5
                                         3.19
                                                                  18
                                                                               22
                                                       115
```

3.2 Create a ML model for Car Price Prediction using Linear Regression-Multiple Variables

The independent variables that affects the price of car are, 1. 'drivewheel' 2. 'wheelbase' 3. 'carlength' 4. 'carwidth' 5. 'curbweight' 6. 'cylindernumber' 7. 'enginesize' 8. 'fuelsystem' 9. 'boreratio' 10. 'horsepower' 11. 'citympg' (negative correlation) 12. 'highwaympg' (negative correlation)

[48]:	drivewheel	wheelbase	carlength	carwidth	curbweight	cylindernumber	\
0	2	88.6	168.8	64.1	2548	4	
1	2	88.6	168.8	64.1	2548	4	
2	2	94.5	171.2	65.5	2823	6	
3	1	99.8	176.6	66.2	2337	4	
4	0	99.4	176.6	66.4	2824	5	
	•••	•••	•••	•••	•••	•••	
200	2	109.1	188.8	68.9	2952	4	
201	2	109.1	188.8	68.8	3049	4	
202	2	109.1	188.8	68.9	3012	6	

```
203
                            109.1
                                                    68.9
                                                                3217
                                                                                     6
                     2
                                        188.8
      204
                     2
                            109.1
                                        188.8
                                                    68.9
                                                                3062
                                                                                     4
           enginesize fuelsystem boreratio horsepower
                                                                       highwaympg
                                                             citympg
      0
                   130
                                  5
                                          3.47
                                                        111
                                                                   21
                                                                                27
      1
                   130
                                  5
                                          3.47
                                                        111
                                                                   21
                                                                               27
      2
                                          2.68
                                                        154
                                                                               26
                   152
                                  5
                                                                   19
      3
                   109
                                  5
                                          3.19
                                                        102
                                                                   24
                                                                                30
      4
                   136
                                  5
                                          3.19
                                                        115
                                                                               22
                                                                   18
      . .
                                                         •••
                                          3.78
                                  5
                                                                   23
                                                                                28
      200
                   141
                                                        114
      201
                   141
                                  5
                                          3.78
                                                        160
                                                                   19
                                                                                25
      202
                                  5
                                          3.58
                                                        134
                   173
                                                                   18
                                                                               23
      203
                   145
                                  3
                                          3.01
                                                        106
                                                                   26
                                                                                27
      204
                   141
                                  5
                                          3.78
                                                        114
                                                                   19
                                                                                25
      [205 rows x 12 columns]
[49]: #dependant variable, y
      У
[49]: 0
             13495.0
      1
             16500.0
      2
             16500.0
      3
             13950.0
      4
             17450.0
      200
             16845.0
             19045.0
      201
      202
             21485.0
      203
             22470.0
      204
             22625.0
      Name: price, Length: 205, dtype: float64
[50]: #import libraries
      from sklearn.linear_model import LinearRegression
[51]: linre=LinearRegression()
      linre
[51]: LinearRegression()
[52]: linre.fit(x,y)
```

[52]: LinearRegression()

```
[53]: #predict the price
      value=[[2,88.6,168.8,64.1,2548,4,130,5,3.47,111,21,27]]
      predicted=linre.predict(value)
      print(predicted)
     [13039.64047938]
     C:\Users\djerb\anaconda3\Lib\site-packages\sklearn\base.py:439: UserWarning: X
     does not have valid feature names, but LinearRegression was fitted with feature
     names
       warnings.warn(
[54]: #check the Accuracy of created ML model
      linre.score(x,y)
[54]: 0.830484708905505
[55]: x.head(1)
[55]:
         drivewheel wheelbase
                                carlength carwidth curbweight cylindernumber
      0
                  2
                          88.6
                                    168.8
                                               64.1
                                                            2548
                     fuelsystem
                                 boreratio horsepower
         enginesize
                                                       citympg
                                                                  highwaympg
      0
                130
                              5
                                      3.47
                                                   111
                                                              21
                                                                          27
[56]: y.head(1)
           13495.0
[56]: 0
      Name: price, dtype: float64
```

4 Result analysis

- 1. The Score of created ML model is good.
- 2. The predicted value lies closer to the actual value, So The created ML model is working good.

5 2- Investigation of the Diamond Dataset

```
[59]: #Import Libraries
  import numpy as np
  import pandas as pd
  import seaborn as sns
  %matplotlib inline
  sns.set_style('whitegrid')
  import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
```

```
from sklearn.preprocessing import LabelEncoder
      from sklearn.preprocessing import StandardScaler
      from sklearn.preprocessing import MinMaxScaler
      from sklearn.decomposition import PCA
      from kneed import KneeLocator
      from sklearn.metrics import silhouette_score
      from sklearn.cluster import KMeans
      from sklearn.cluster import DBSCAN
      from sklearn.neighbors import KNeighborsClassifier
      from sklearn.model_selection import GridSearchCV
      from sklearn import preprocessing
      from sklearn import metrics
      from sklearn.metrics import accuracy_score
      from sklearn.metrics import classification report, confusion matrix
      from sklearn.metrics import mean squared error, r2 score, mean absolute error
      from sklearn.model_selection import cross_val_score
      import warnings
      warnings.filterwarnings('ignore')
[61]: diamonds = pd.read_csv('C:/Users/djerb/Downloads/Diamonds/Diamonds/diamonds.
       ⇔csv¹)
      diamonds.head()
[61]:
        Unnamed: 0 carat
                               cut color clarity depth table price
                                                                          Х
                     0.23
                                                   61.5
                                                          55.0
                  1
                             Ideal
                                       Ε
                                             SI2
                                                                   326 3.95 3.98
                                                   59.8
                     0.21 Premium
                                       Ε
                                             SI1
                                                          61.0
                                                                   326 3.89 3.84
      1
      2
                  3
                     0.23
                               Good
                                       Ε
                                             VS1
                                                   56.9
                                                          65.0
                                                                   327
                                                                       4.05
                                                                             4.07
      3
                 4
                     0.29 Premium
                                       Ι
                                             VS2
                                                   62.4
                                                          58.0
                                                                   334 4.20 4.23
                     0.31
                              Good
                                             SI2
                                                   63.3
                                                          58.0
                                                                   335 4.34 4.35
           z
      0 2.43
      1 2.31
      2 2.31
      3 2.63
      4 2.75
[62]: diamonds["size"] = diamonds["x"] * diamonds["y"] * diamonds["z"]
      col_names = ['price','carat', 'size', 'depth', 'table', 'color', 'clarity', __
      diamonds = diamonds[col_names]
      diamonds.head()
[62]:
        price carat
                                 depth table color clarity
                                                                  cut
                            size
           326
                0.23 38.202030
                                  61.5
                                          55.0
                                                  Ε
                                                        SI2
                                                                Ideal
```

```
0.21 34.505856
     2
          327
              0.23 38.076885
                                  56.9
                                         65.0
                                                  Ε
                                                       VS1
                                                               Good
                0.29 46.724580
     3
          334
                                  62.4
                                         58.0
                                                  Ι
                                                       VS2 Premium
                0.31 51.917250
     4
          335
                                  63.3
                                         58.0
                                                  J
                                                        SI2
                                                               Good
[63]: #Encoding categorical features
     encoder = LabelEncoder()
     encoder.fit(diamonds['cut'])
     diamonds['cut'] = encoder.transform(diamonds['cut'])
     encoder.fit(diamonds['color'])
     diamonds['color'] = encoder.transform(diamonds['color'])
     encoder.fit(diamonds['clarity'])
     diamonds['clarity'] = encoder.transform(diamonds['clarity'])
     diamonds.head()
[63]:
                           size depth table color clarity
        price carat
                                  61.5
          326
                0.23 38.202030
                                         55.0
               0.21 34.505856
     1
          326
                                  59.8
                                         61.0
                                                           2
     2
          327 0.23 38.076885
                                  56.9
                                         65.0
                                                   1
                                                           4
                                                                1
     3
               0.29 46.724580
                                  62.4
                                         58.0
                                                   5
                                                           5
                                                                3
          334
     4
                0.31 51.917250
                                  63.3
                                         58.0
                                                   6
                                                           3
          335
                                                                1
[64]: #Split dataset in train and test Data
     df = diamonds.copy()
     #"cut" is my predictor variable
     X = df.drop('cut',axis=1)
     #Label or target variable
     y = df['cut']
     #Define the split in Training/Test and their proportions
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, __
      →random_state = 42)
     print(X_train.shape, y_train.shape)
     (43152, 7) (43152,)
[65]: df.info()
     df.columns
     df.shape
     df.dtypes
```

59.8

61.0

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1

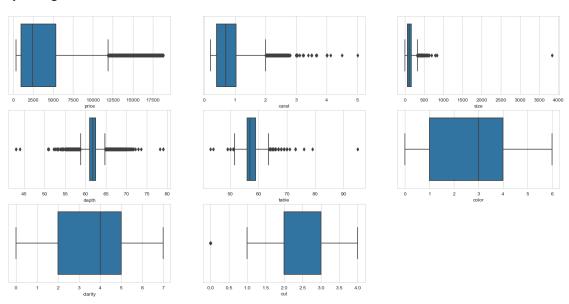
326

```
df.isnull().sum()
fig = plt.figure(figsize=(20,20))
for col in range(len(df.columns)) :
    fig.add_subplot(6,3,col+1)
    sns.boxplot(x=df.iloc[:, col])
plt.show()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 8 columns):

#	Column	Non-Nu	ıll Count	Dtype				
0	price	53940	non-null	int64				
1	carat	53940	non-null	float64				
2	size	53940	non-null	float64				
3	depth	53940	non-null	float64				
4	table	53940	non-null	float64				
5	color	53940	non-null	int32				
6	clarity	53940	non-null	int32				
7	cut	53940	non-null	int32				
dtype	es: float	34(4),	int32(3),	int64(1)				
0.7.10								

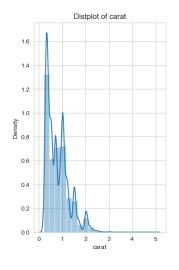
memory usage: 2.7 MB



```
[68]: df.describe().T

#Check correlation between different features
df.corr()
```

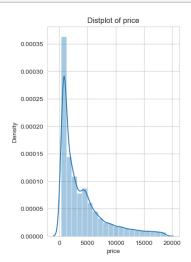
```
[68]:
                                               depth
                                                         table
                                                                   color
                                                                          clarity \
                 price
                           carat
                                      size
              1.000000 \quad 0.921591 \quad 0.902385 \quad -0.010647 \quad 0.127134 \quad 0.172511 \quad -0.071535
     price
     carat
              0.921591
                        1.000000 0.976308 0.028224 0.181618 0.291437 -0.214290
     size
              0.902385 0.976308 1.000000 0.009157
                                                     0.167400
                                                               0.284267 -0.206632
     depth
             -0.010647
                        0.028224 0.009157 1.000000 -0.295779
                                                               0.047279 -0.053080
     table
              1.000000 0.026465 -0.088223
     color
              0.172511 0.291437
                                  0.284267 0.047279 0.026465
                                                               1.000000 -0.027795
     clarity -0.071535 -0.214290 -0.206632 -0.053080 -0.088223 -0.027795
                                                                         1.000000
     cut
              0.039860 0.017124 0.021440 -0.194249 0.150327
                                                               0.000304 0.028235
                   cut
              0.039860
     price
              0.017124
     carat
     size
              0.021440
     depth
             -0.194249
     table
              0.150327
     color
              0.000304
     clarity
              0.028235
     cut
              1.000000
[71]: plt.figure(1 , figsize = (15 , 6))
     n = 0
     for x in ['carat' , 'price' , 'size']:
         n += 1
         plt.subplot(1 , 3 , n)
         plt.subplots_adjust(hspace = 0.5 , wspace = 0.5)
```

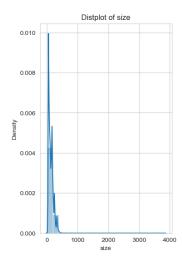


plt.show()

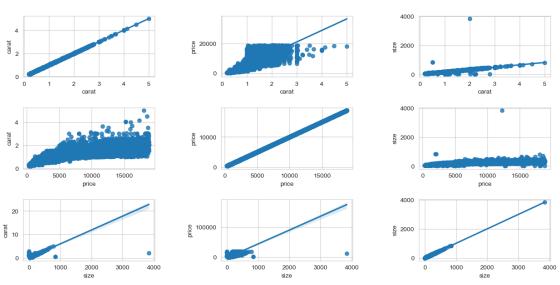
sns.distplot(df[x], bins = 20)

plt.title('Distplot of {}'.format(x))





```
[72]: #Plot to see relationship between the features 'carat', 'price', 'size'
plt.figure(1 , figsize = (15 , 7))
n = 0
for x in ['carat' , 'price' , 'size']:
    for y in ['carat' , 'price' , 'size']:
        n += 1
        plt.subplot(3 , 3 , n)
        plt.subplots_adjust(hspace = 0.5 , wspace = 0.5)
        sns.regplot(x = x , y = y , data = df)
        plt.ylabel(y.split()[0]+' '+y.split()[1] if len(y.split()) > 1 else y )
plt.show()
```



```
[73]: #Normalize the data and avoid the problem that generates outliers
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(df)
```

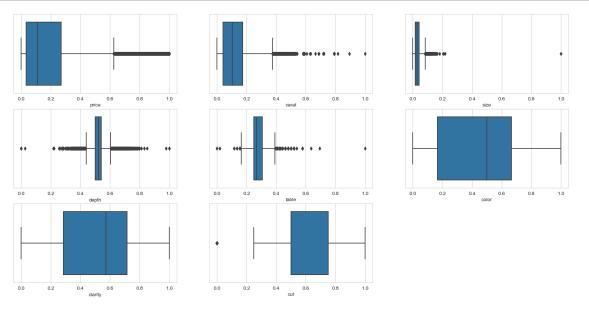
```
[74]: df1 = pd.DataFrame(X_scaled)
```

```
[75]: df1
```

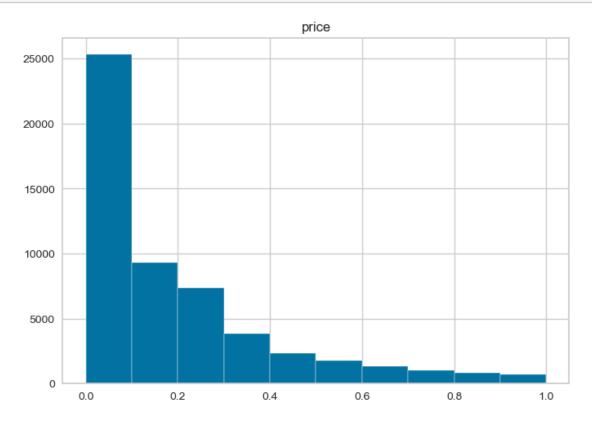
```
[75]:
                    0
                              1
                                        2
                                                   3
                                                             4
                                                                       5
                                                                                  6
                                                                                    \
      0
             0.000000 0.006237
                                 0.009947 0.513889
                                                      0.230769 0.166667
                                                                          0.428571
                                                                0.166667
      1
             0.000000
                      0.002079
                                 0.008985
                                           0.466667
                                                      0.346154
                                                                          0.285714
      2
             0.000054
                      0.006237
                                 0.009914
                                            0.386111
                                                      0.423077
                                                                0.166667
                                                                          0.571429
      3
             0.000433
                       0.018711
                                 0.012166
                                            0.538889
                                                      0.288462
                                                                0.833333
                                                                          0.714286
             0.000487
                       0.022869
                                 0.013518
                                           0.563889
                                                      0.288462
                                                                1.000000
                                                                          0.428571
                                                 •••
                                                         •••
                                                                          0.285714
      53935
             0.131427
                       0.108108 0.030183
                                            0.494444
                                                      0.269231
                                                                0.000000
      53936
            0.131427
                       0.108108 0.030753
                                           0.558333
                                                      0.230769
                                                                0.000000
                                                                          0.285714
```

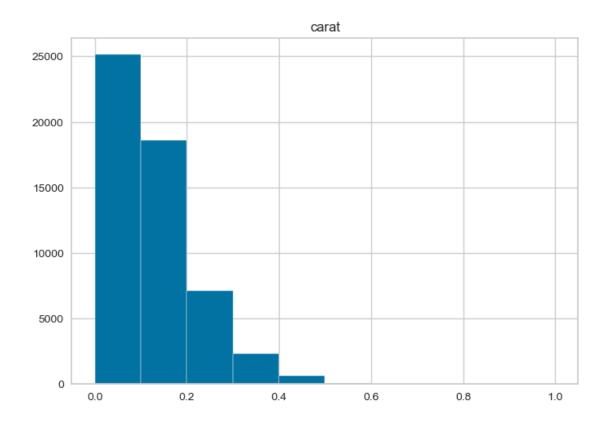
```
53937
      0.131427 0.103950 0.029800 0.550000
                                              0.326923 0.000000
                                                                  0.285714
53938
      0.131427
                0.137214
                          0.036652 0.500000
                                              0.288462 0.666667
                                                                  0.428571
53939
      0.131427 0.114345
                                              0.230769 0.000000
                          0.032435 0.533333
                                                                  0.428571
         7
0
      0.50
      0.75
1
2
      0.25
3
      0.75
4
      0.25
53935 0.50
53936 0.25
53937
      1.00
53938
      0.75
53939
      0.50
```

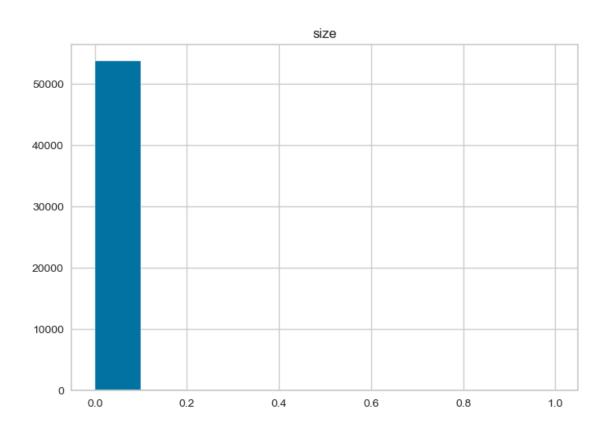
[53940 rows x 8 columns]

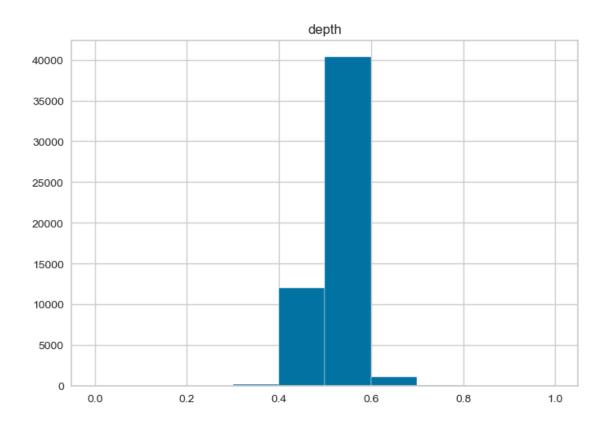


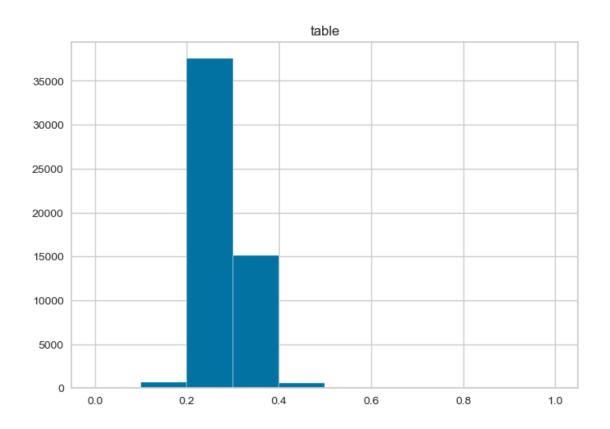
```
[83]: for col in df1:
    df1[[col]].hist()
```

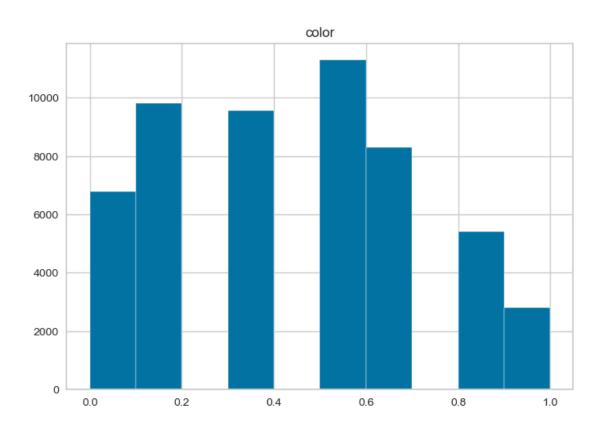


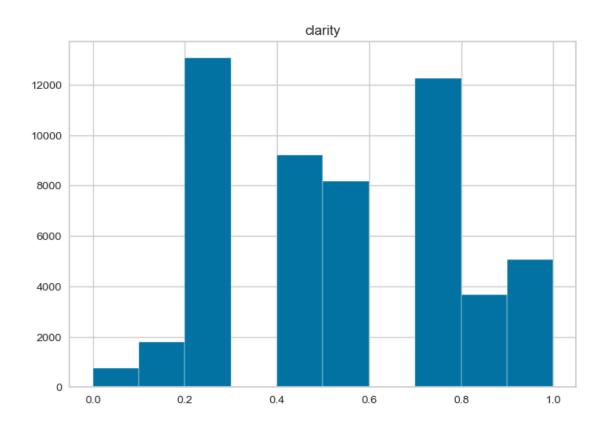


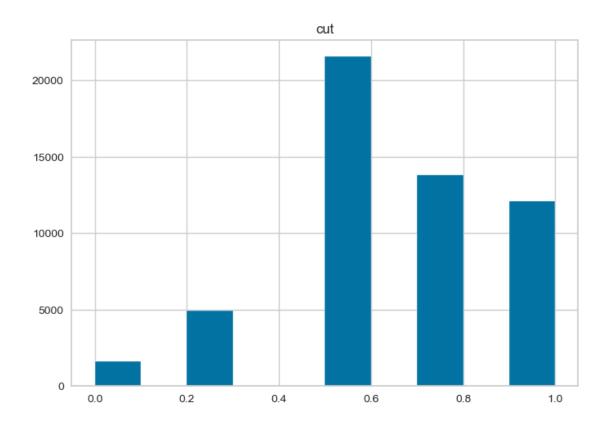












```
AttributeError Traceback (most recent call last)

Cell In[91], line 6
3 model = KMeans(random_state=1)
4 visualizer = KElbowVisualizer(model, k=(2,10))

----> 6 visualizer.fit(df1)
7 visualizer.show()
```

```
8 plt.show()
File ~\anaconda3\Lib\site-packages\yellowbrick\cluster\elbow.py:339, in_
 337 # Set the k value and fit the model
    338 self.estimator.set params(n clusters=k)
--> 339 self.estimator.fit(X, **kwargs)
    341 # Append the time and score to our plottable metrics
    342 self.k timers .append(time.time() - start)
File ~\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1468, in KMeans.

fit(self, X, y, sample_weight)
   1465
           print("Initialization complete")
   1467 # run a k-means once
-> 1468 labels, inertia, centers, n_iter_ = kmeans_single(
   1469
   1470
           sample_weight,
   1471
           centers_init,
   1472
           max_iter=self.max_iter,
   1473
           verbose=self.verbose,
   1474
           tol=self. tol,
           n threads=self. n threads,
   1475
   1476 )
   1478 # determine if these results are the best so far
   1479 # we chose a new run if it has a better inertia and the clustering is
  1480 # different from the best so far (it's possible that the inertia is
   1481 # slightly better even if the clustering is the same with potentially
   1482 # permuted labels, due to rounding errors)
   1483 if best inertia is None or (
   1484
           inertia < best_inertia</pre>
   1485
           and not _is_same_clustering(labels, best_labels, self.n_clusters)
   1486 ):
File ~\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:679, in_
 → kmeans_single_lloyd(X, sample_weight, centers_init, max_iter, verbose, tol,_
 675 strict_convergence = False
    677 # Threadpoolctl context to limit the number of threads in second level of
    678 # nested parallelism (i.e. BLAS) to avoid oversubscription.
--> 679 with threadpool_limits(limits=1, user_api="blas"):
    680
           for i in range(max_iter):
    681
               lloyd_iter(
    682
                   Х,
    683
                    sample_weight,
   (...)
    689
                   n threads,
               )
    690
```

```
File ~\anaconda3\Lib\site-packages\sklearn\utils\fixes.py:139, in_
 →threadpool_limits(limits, user_api)
            return controller.limit(limits=limits, user_api=user_api)
    137
    138 else:
            return threadpoolctl.threadpool limits(limits=limits,
--> 139
 ⇔user_api=user_api)
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:171, in threadpool_limits.
 →__init__(self, limits, user_api)
    167 def __init__(self, limits=None, user_api=None):
            self._limits, self._user_api, self._prefixes = \
                self._check_params(limits, user_api)
    169
            self._original_info = self._set_threadpool_limits()
--> 171
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:268, in threadpool_limits.
 ⇔_set_threadpool_limits(self)
    265 if self._limits is None:
            return None
    266
--> 268 modules = _ThreadpoolInfo(prefixes=self._prefixes,
                                  user api=self. user api)
    269
    270 for module in modules:
            # self. limits is a dict {key: num threads} where key is either
    271
            # a prefix or a user_api. If a module matches both, the limit
    272
    273
            # corresponding to the prefix is chosed.
    274
            if module.prefix in self._limits:
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:340, in ThreadpoolInfo.

    init__(self, user_api, prefixes, modules)

            self.user_api = [] if user_api is None else user_api
    337
    339
            self.modules = []
--> 340
            self._load_modules()
    341
            self._warn_if_incompatible_openmp()
    342 else:
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:373, in ThreadpoolInfo.
 → load modules(self)
            self. find modules with dyld()
    372 elif sys.platform == "win32":
--> 373
           self._find_modules_with_enum_process_module_ex()
    374 else:
            self._find_modules_with_dl_iterate_phdr()
    375
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:485, in _ThreadpoolInfo.
 → find modules with enum process module ex(self)
                filepath = buf.value
    482
                # Store the module if it is supported and selected
    484
--> 485
                self._make_module_from_path(filepath)
    486 finally:
```

```
kernel_32.CloseHandle(h_process)
      File ~\anaconda3\Lib\site-packages\threadpoolctl.py:515, in ThreadpoolInfo.
        →_make_module_from_path(self, filepath)
           513 if prefix in self.prefixes or user api in self.user api:
                   module_class = globals()[module_class]
           514
       --> 515
                   module = module_class(filepath, prefix, user_api, internal_api)
                   self.modules.append(module)
           516
      File ~\anaconda3\Lib\site-packages\threadpoolctl.py:606, in _Module.

    init_(self, filepath, prefix, user_api, internal_api)

           604 self.internal_api = internal_api
           605 self._dynlib = ctypes.CDLL(filepath, mode=_RTLD_NOLOAD)
       --> 606 self.version = self.get_version()
           607 self.num_threads = self.get_num_threads()
           608 self._get_extra_info()
      File ~\anaconda3\Lib\site-packages\threadpoolctl.py:646, in _OpenBLASModule.
        →get_version(self)
           643 get_config = getattr(self._dynlib, "openblas_get_config",
                                    lambda: None)
           645 get_config.restype = ctypes.c_char_p
       --> 646 config = get_config().split()
           647 if config[0] == b"OpenBLAS":
           648
                   return config[1].decode("utf-8")
       AttributeError: 'NoneType' object has no attribute 'split'
[82]: kmeans kwargs = {
          "init": "random",
          "n init": 10,
          "max iter": 300,
          "random_state": 42,
      }
      # A list holds the SSE values for each k
      sse = []
      for k in range(1, 11):
          kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
          kmeans.fit(df1)
          sse.append(kmeans.inertia_)
                                                 Traceback (most recent call last)
       AttributeError
      Cell In[82], line 12
            10 for k in range(1, 11):
                  kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
```

487

```
---> 12
           kmeans.fit(df1)
    13
           sse.append(kmeans.inertia_)
File ~\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1468, in KMeans.
 print("Initialization complete")
   1465
   1467 # run a k-means once
-> 1468 labels, inertia, centers, n_iter_ = kmeans_single(
   1469
           Χ.
   1470
           sample_weight,
   1471
           centers_init,
   1472
           max_iter=self.max_iter,
           verbose=self.verbose,
   1473
  1474
           tol=self. tol,
           n_threads=self._n_threads,
   1475
  1476 )
   1478 # determine if these results are the best so far
  1479 # we chose a new run if it has a better inertia and the clustering is
   1480 # different from the best so far (it's possible that the inertia is
   1481 # slightly better even if the clustering is the same with potentially
   1482 # permuted labels, due to rounding errors)
   1483 if best inertia is None or (
           inertia < best inertia
   1485
           and not _is_same_clustering(labels, best_labels, self.n_clusters)
   1486 ):
File ~\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:679, in_
 → kmeans_single_lloyd(X, sample_weight, centers_init, max_iter, verbose, tol,_
 675 strict convergence = False
    677 # Threadpoolctl context to limit the number of threads in second level of
    678 # nested parallelism (i.e. BLAS) to avoid oversubscription.
--> 679 with threadpool_limits(limits=1, user_api="blas"):
    680
           for i in range(max_iter):
               lloyd_iter(
    681
    682
                   Χ,
    683
                    sample_weight,
   (...)
    689
                   n_threads,
               )
    690
File ~\anaconda3\Lib\site-packages\sklearn\utils\fixes.py:139, in_
 →threadpool_limits(limits, user_api)
           return controller.limit(limits=limits, user_api=user_api)
    137
    138 else:
--> 139
           return threadpoolctl.threadpool_limits(limits=limits,_
 ⇒user api=user api)
```

```
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:171, in threadpool limits.
 →__init__(self, limits, user_api)
    167 def __init__(self, limits=None, user_api=None):
           self._limits, self._user_api, self._prefixes = \
               self. check params(limits, user api)
    169
           self._original_info = self._set_threadpool_limits()
--> 171
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:268, in threadpool_limits.
 ⇔ set threadpool limits(self)
    265 if self._limits is None:
           return None
    266
--> 268 modules = _ThreadpoolInfo(prefixes=self._prefixes,
                                 user_api=self._user_api)
    270 for module in modules:
           # self._limits is a dict {key: num_threads} where key is either
    271
           # a prefix or a user_api. If a module matches both, the limit
    272
    273
           # corresponding to the prefix is chosed.
    274
           if module.prefix in self._limits:
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:340, in ThreadpoolInfo.
 self.user api = [] if user api is None else user api
           self.modules = []
    339
--> 340
           self._load_modules()
           self._warn_if_incompatible_openmp()
    341
    342 else:
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:373, in _ThreadpoolInfo.
 → load modules(self)
           self._find_modules_with_dyld()
    372 elif sys.platform == "win32":
--> 373
           self._find_modules_with_enum_process_module_ex()
    374 else:
           self._find_modules_with_dl_iterate_phdr()
    375
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:485, in _ThreadpoolInfo.
 → find modules with enum process module ex(self)
               filepath = buf.value
               # Store the module if it is supported and selected
    484
               self._make_module_from_path(filepath)
--> 485
   486 finally:
           kernel_32.CloseHandle(h_process)
    487
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:515, in ThreadpoolInfo.
 → make module from path(self, filepath)
    513 if prefix in self.prefixes or user_api in self.user_api:
    514
           module_class = globals()[module_class]
--> 515
           module = module_class(filepath, prefix, user_api, internal_api)
```

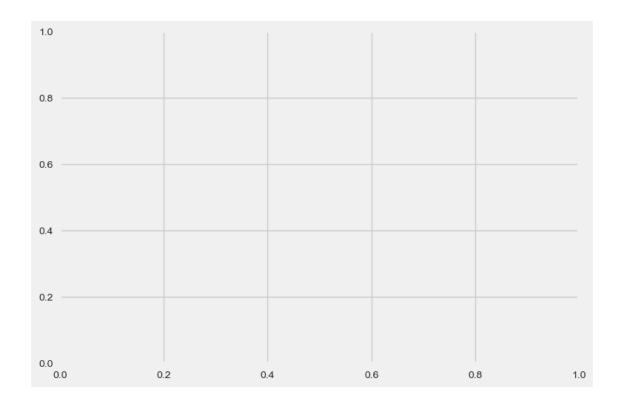
```
516
            self.modules.append(module)
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:606, in _Module.
 init_(self, filepath, prefix, user_api, internal_api)
    604 self.internal api = internal api
    605 self._dynlib = ctypes.CDLL(filepath, mode=_RTLD_NOLOAD)
--> 606 self.version = self.get version()
    607 self.num_threads = self.get_num_threads()
    608 self._get_extra_info()
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:646, in _OpenBLASModule.

get_version(self)
    643 get_config = getattr(self._dynlib, "openblas_get_config",
    644
                             lambda: None)
    645 get_config.restype = ctypes.c_char_p
--> 646 config = get_config().split()
    647 if config[0] == b"OpenBLAS":
    648
           return config[1].decode("utf-8")
AttributeError: 'NoneType' object has no attribute 'split'
```

```
[86]: plt.style.use("fivethirtyeight")
  plt.plot(range(1, 11), sse)
  plt.xticks(range(1, 11))
  plt.xlabel("Number of Clusters")
  plt.ylabel("SSE")
  plt.show()
```

```
ValueError
                                          Traceback (most recent call last)
Cell In[86], line 2
      1 plt.style.use("fivethirtyeight")
----> 2 plt.plot(range(1, 11), sse)
      3 plt.xticks(range(1, 11))
      4 plt.xlabel("Number of Clusters")
File ~\anaconda3\Lib\site-packages\matplotlib\pyplot.py:3578, in plot(scalex,_
 ⇔scaley, data, *args, **kwargs)
   3570 @_copy_docstring_and_deprecators(Axes.plot)
   3571 def plot(
   3572
            *args: float | ArrayLike | str,
   (...)
   3576
            **kwargs,
   3577 ) -> list[Line2D]:
-> 3578 return gca().plot(
   3579
               *args,
   3580
               scalex=scalex,
```

```
3581
                scaley=scaley,
   3582
                **({"data": data} if data is not None else {}),
   3583
                **kwargs,
   3584
            )
File ~\anaconda3\Lib\site-packages\matplotlib\axes\_axes.py:1721, in Axes.
 splot(self, scalex, scaley, data, *args, **kwargs)
   1478 """
   1479 Plot y versus x as lines and/or markers.
   1480
   (...)
   1718 (``'green'``) or hex strings (``'#008000'``).
   1719 """
   1720 kwargs = cbook.normalize_kwargs(kwargs, mlines.Line2D)
-> 1721 lines = [*self._get_lines(self, *args, data=data, **kwargs)]
   1722 for line in lines:
   1723
            self.add_line(line)
File ~\anaconda3\Lib\site-packages\matplotlib\axes\_base.py:303, in_
 → process plot var args. call (self, axes, data, *args, **kwargs)
            this += args[0],
            args = args[1:]
    302
--> 303 yield from self._plot_args(
            axes, this, kwargs, ambiguous fmt datakey=ambiguous fmt datakey)
File ~\anaconda3\Lib\site-packages\matplotlib\axes\_base.py:499, in_
 → process plot var args. plot args(self, axes, tup, kwargs, return_kwargs, ___
 →ambiguous_fmt_datakey)
    496
            axes.yaxis.update_units(y)
    498 if x.shape[0] != y.shape[0]:
            raise ValueError(f"x and y must have same first dimension, but "
--> 499
                             f"have shapes {x.shape} and {y.shape}")
    500
    501 if x.ndim > 2 or y.ndim > 2:
    502
            raise ValueError(f"x and y can be no greater than 2D, but have "
    503
                             f"shapes {x.shape} and {y.shape}")
ValueError: x and y must have same first dimension, but have shapes (10,) and
 \hookrightarrow (0,)
```



```
[94]: kl = KneeLocator(
          range(1, 11), sse, curve="convex", direction="decreasing"
)
kl.elbow
```

```
ValueError
                                          Traceback (most recent call last)
Cell In[94], line 1
----> 1 kl = KneeLocator(
           range(1, 11), sse, curve="convex", direction="decreasing"
      3)
      5 kl.elbow
File ~\anaconda3\Lib\site-packages\kneed\knee_locator.py:171, in KneeLocator.
 →__init__(self, x, y, S, curve, direction, interp_method, online, u
 →polynomial_degree)
    169 # Step 1: fit a smooth line
    170 if interp_method == "interp1d":
            uspline = interpolate.interp1d(self.x, self.y)
--> 171
            self.Ds_y = uspline(self.x)
    173 elif interp_method == "polynomial":
```

```
File ~\anaconda3\Lib\site-packages\scipy\interpolate\_interpolate.py:494, in_
 interp1d.__init__(self, x, y, kind, axis, copy, bounds_error, fill_value, ∪
 →assume_sorted)
    490 def __init__(self, x, y, kind='linear', axis=-1,
                     copy=True, bounds_error=None, fill_value=np.nan,
    491
    492
                     assume_sorted=False):
    493
            """ Initialize a 1-D linear interpolation class."""
            _Interpolator1D.__init__(self, x, y, axis=axis)
--> 494
            self.bounds_error = bounds_error # used by fill_value setter
    496
    497
            self.copy = copy
File ~\anaconda3\Lib\site-packages\scipy\interpolate\_polyint.py:56, in_
 → Interpolator1D. __init__(self, xi, yi, axis)
     54 self.dtype = None
     55 if yi is not None:
            self._set_yi(yi, xi=xi, axis=axis)
---> 56
File ~\anaconda3\Lib\site-packages\scipy\interpolate\_polyint.py:126, in_
 →_Interpolator1D._set_yi(self, yi, xi, axis)
    124
            shape = (1,)
    125 if xi is not None and shape[axis] != len(xi):
            raise ValueError("x and y arrays must be equal in length along "
--> 126
                             "interpolation axis.")
    127
    129 self._y_axis = (axis % yi.ndim)
    130 self._y_extra_shape = yi.shape[:self._y_axis]+yi.shape[self._y_axis+1:]
ValueError: x and y arrays must be equal in length along interpolation axis.
```

```
[95]: #Model building using KMeans
kmeans = KMeans(n_clusters=5, max_iter=600, algorithm = 'auto')
kmeans.fit(df1)
```

```
Traceback (most recent call last)
AttributeError
Cell In[95], line 3
      1 #Model building using KMeans
      2 kmeans = KMeans(n_clusters=5, max_iter=600, algorithm = 'auto')
----> 3 kmeans.fit(df1)
File ~\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1468, in KMeans.

fit(self, X, y, sample_weight)
           print("Initialization complete")
   1465
   1467 # run a k-means once
-> 1468 labels, inertia, centers, n_iter_ = kmeans_single(
   1469
            sample_weight,
   1470
   1471
           centers_init,
```

```
1472
            max_iter=self.max_iter,
   1473
            verbose=self.verbose,
   1474
            tol=self._tol,
            n_threads=self._n_threads,
   1475
   1476 )
   1478 # determine if these results are the best so far
   1479 # we chose a new run if it has a better inertia and the clustering is
   1480 # different from the best so far (it's possible that the inertia is
   1481 # slightly better even if the clustering is the same with potentially
   1482 # permuted labels, due to rounding errors)
   1483 if best_inertia is None or (
            inertia < best_inertia</pre>
   1484
   1485
            and not _is_same_clustering(labels, best_labels, self.n_clusters)
   1486 ):
File ~\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:679, in_
 weight, centers_init, max_iter, verbose, tol,
 →n threads)
    675 strict_convergence = False
    677 # Threadpoolctl context to limit the number of threads in second level of
    678 # nested parallelism (i.e. BLAS) to avoid oversubscription.
--> 679 with threadpool_limits(limits=1, user_api="blas"):
            for i in range(max_iter):
    680
    681
                lloyd_iter(
    682
                    Х,
    683
                    sample_weight,
   (...)
    689
                    n_threads,
    690
                )
File ~\anaconda3\Lib\site-packages\sklearn\utils\fixes.py:139, in_
 ⇔threadpool limits(limits, user api)
    137
            return controller.limit(limits=limits, user_api=user_api)
    138 else:
            return threadpoolctl.threadpool_limits(limits=limits,__
--> 139
 ⇔user_api=user_api)
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:171, in threadpool_limits.

    init_ (self, limits, user_api)

    167 def __init__(self, limits=None, user_api=None):
            self._limits, self._user_api, self._prefixes = \
    168
    169
                self._check_params(limits, user_api)
--> 171
            self._original_info = self._set_threadpool_limits()
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:268, in threadpool limits.
 ⇔ set threadpool limits(self)
    265 if self. limits is None:
           return None
    266
```

```
--> 268 modules = _ThreadpoolInfo(prefixes=self._prefixes,
                                 user_api=self._user_api)
    269
    270 for module in modules:
           # self._limits is a dict {key: num_threads} where key is either
           # a prefix or a user api. If a module matches both, the limit
    272
    273
           # corresponding to the prefix is chosed.
           if module.prefix in self. limits:
    274
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:340, in ThreadpoolInfo.
 self.user_api = [] if user_api is None else user_api
    337
           self.modules = []
    339
--> 340
           self._load_modules()
           self._warn_if_incompatible_openmp()
    341
    342 else:
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:373, in _ThreadpoolInfo.
 →_load_modules(self)
           self._find_modules_with_dyld()
    371
    372 elif sys.platform == "win32":
--> 373
           self._find_modules_with_enum_process_module_ex()
    374 else:
           self._find_modules_with_dl_iterate_phdr()
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:485, in _ThreadpoolInfo.
 → find modules with enum process module ex(self)
    482
               filepath = buf.value
               # Store the module if it is supported and selected
    484
               self._make_module_from_path(filepath)
--> 485
    486 finally:
    487
           kernel_32.CloseHandle(h_process)
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:515, in ThreadpoolInfo.
 →_make_module_from_path(self, filepath)
    513 if prefix in self.prefixes or user api in self.user api:
           module class = globals()[module class]
    514
           module = module class(filepath, prefix, user api, internal api)
--> 515
    516
           self.modules.append(module)
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:606, in _Module.
 init_(self, filepath, prefix, user_api, internal_api)
    604 self.internal_api = internal_api
    605 self._dynlib = ctypes.CDLL(filepath, mode=_RTLD_NOLOAD)
--> 606 self.version = self.get_version()
    607 self.num_threads = self.get_num_threads()
    608 self._get_extra_info()
```

```
File ~\anaconda3\Lib\site-packages\threadpoolctl.py:646, in _OpenBLASModule.

    get_version(self)

           643 get_config = getattr(self._dynlib, "openblas_get_config",
                                    lambda: None)
           645 get config.restype = ctypes.c char p
       --> 646 config = get config().split()
           647 if config[0] == b"OpenBLAS":
                   return config[1].decode("utf-8")
           648
      AttributeError: 'NoneType' object has no attribute 'split'
[96]: #Use scatterplot to show clusters via PCA
      plt.scatter(df2[:, 0], df2[:, 1],
                  c= kmeans.labels_.astype(float), edgecolor='none', alpha=0.5,
                  cmap=plt.cm.get_cmap('Spectral', 10))
      plt.xlabel('PCA1')
      plt.ylabel('PCA2')
      plt.title('Diamonds clusters using KMEANS')
      plt.colorbar();
       AttributeError
                                                 Traceback (most recent call last)
      Cell In[96], line 3
             1 #Use scatterplot to show clusters via PCA
             2 plt.scatter(df2[:, 0], df2[:, 1],
       ----> 3
                           c= kmeans.labels_.astype(float), edgecolor='none', alpha=0.,
                           cmap=plt.cm.get_cmap('Spectral', 10))
             5 plt.xlabel('PCA1')
             6 plt.ylabel('PCA2')
      AttributeError: 'KMeans' object has no attribute 'labels_'
[98]: df1["cluster"] = kmeans.labels_.astype(float)
      df1
       AttributeError
                                                 Traceback (most recent call last)
      Cell In[98], line 1
       ----> 1 df1["cluster"] = kmeans.labels_.astype(float)
             2 df1
      AttributeError: 'KMeans' object has no attribute 'labels '
[99]: # Number of clusters in labels, ignoring noise if present.
      labels_kmeans = kmeans.labels_
```

```
n_clusters_ = len(set(labels_kmeans)) - (1 if -1 in labels_kmeans else 0)
n_noise_ = list(labels_kmeans).count(-1)

print("Estimated number of clusters: %d" % n_clusters_)
print("Estimated number of noise points: %d" % n_noise_)
```

```
AttributeError Traceback (most recent call last)

Cell In[99], line 2

1 # Number of clusters in labels, ignoring noise if present.

----> 2 labels_kmeans = kmeans.labels_

3 n_clusters_ = len(set(labels_kmeans)) - (1 if -1 in labels_kmeans else 4 n_noise_ = list(labels_kmeans).count(-1)

AttributeError: 'KMeans' object has no attribute 'labels_'
```

```
[101]: for c in df1:
        grid= sns.FacetGrid(df1, col='cluster')
        grid.map(plt.hist, c)
        kmeans=KMeans(5)
        kmeans.fit_predict(df1)
        y_pred = kmeans.predict(df1)
        #preds = kmeans.labels_
        data = pd.DataFrame(df)
        data['cluster'] = y_pred
        data.head(10)
```

```
KeyError Traceback (most recent call last)
File ~\anaconda3\Lib\site-packages\pandas\core\indexes\base.py:3791, in Index.

Get_loc(self, key)

3790 try:

-> 3791    return self._engine.get_loc(casted_key)

3792 except KeyError as err:

File index.pyx:152, in pandas._libs.index.IndexEngine.get_loc()

File index.pyx:181, in pandas._libs.index.IndexEngine.get_loc()

File pandas\_libs\hashtable_class_helper.pxi:7080, in pandas._libs.hashtable.

GPyObjectHashTable.get_item()

File pandas\_libs\hashtable_class_helper.pxi:7088, in pandas._libs.hashtable.

GPyObjectHashTable.get_item()

KeyError: 'cluster'
```

```
The above exception was the direct cause of the following exception:
                                             Traceback (most recent call last)
KeyError
Cell In[101], line 2
      1 for c in df1:
            grid= sns.FacetGrid(df1, col='cluster')
            grid.map(plt.hist, c)
      4 kmeans=KMeans(5)
File ~\anaconda3\Lib\site-packages\seaborn\axisgrid.py:396, in FacetGrid.
 →__init__(self, data, row, col, hue, col_wrap, sharex, sharey, height, aspect, palette, row_order, col_order, hue_order, hue_kws, dropna, legend_out,
 →despine, margin_titles, xlim, ylim, subplot_kws, gridspec_kws)
            col names = []
    395 else:
--> 396
            col_names = categorical_order(data[col], col_order)
    398 # Additional dict of kwarg -> list of values for mapping the hue var
    399 hue kws = hue kws if hue kws is not None else {}
File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:3893, in DataFrame.

    getitem (self, key)

   3891 if self.columns.nlevels > 1:
            return self._getitem_multilevel(key)
-> 3893 indexer = self.columns.get_loc(key)
   3894 if is_integer(indexer):
   3895
            indexer = [indexer]
File ~\anaconda3\Lib\site-packages\pandas\core\indexes\base.py:3798, in Index.
 →get_loc(self, key)
   3793
            if isinstance(casted_key, slice) or (
   3794
                 isinstance(casted_key, abc.Iterable)
   3795
                 and any(isinstance(x, slice) for x in casted_key)
   3796
            ):
   3797
                 raise InvalidIndexError(key)
-> 3798
            raise KeyError(key) from err
   3799 except TypeError:
   3800
            # If we have a listlike key, _check_indexing error will raise
            # InvalidIndexError. Otherwise we fall through and re-raise
   3801
   3802
            # the TypeError.
   3803
            self._check_indexing_error(key)
KeyError: 'cluster'
```

```
[102]: #Use scatterplot to show clusters via KMEANS
    plt.figure(figsize=(8,8))
    sns.scatterplot(x='price',y='carat',hue="cluster",data=data,palette='Paired_r')
```

```
plt.title('Diamonds clusters using KMEANS')
plt.show()
```

```
NameError Traceback (most recent call last)

Cell In[102], line 3

1 #Use scatterplot to show clusters via KMEANS

2 plt.figure(figsize=(8,8))

----> 3 sns.

scatterplot(x='price',y='carat',hue="cluster",data=data,palette='Paired_r')

4 plt.title('Diamonds clusters using KMEANS')

5 plt.show()

NameError: name 'data' is not defined
```

<Figure size 800x800 with 0 Axes>

6 Using KNN Algorithm to predict if a person will have diabetes or not

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

```
[105]: data = pd.read_csv(r"C:\Users\djerb\Downloads\Diabetes\Diabetes\diabetes.csv") data.head()
```

```
[105]:
         Pregnancies Glucose BloodPressure SkinThickness
                                                           Insulin
                                                                     BMI \
                                                                 0 33.6
      0
                   6
                         148
                                         72
                                                       35
      1
                   1
                          85
                                         66
                                                        29
                                                                 0 26.6
      2
                   8
                         183
                                         64
                                                        0
                                                                0 23.3
      3
                   1
                         89
                                         66
                                                        23
                                                                94 28.1
                         137
                                         40
                                                        35
                                                               168 43.1
```

```
DiabetesPedigreeFunction Age Outcome 0 0.627 50 1 1 0.351 31 0
```

```
2 0.672 32 1
3 0.167 21 0
4 2.288 33 1
```

```
[106]: zero_not_accepted = ['Glucose', 'BloodPressure', 'SkinThickness', 'BMI', 'Insulin']
# for col in zero_not_accepted:
# for i in data[col]:
# if i==0:
# colSum = sum(data[col])
# meanCol=colSum/len(data[col])
# data[col]=meanCol

for col in zero_not_accepted:
    data[col]= data[col].replace(0,np.NaN)
    mean = int(data[col].mean(skipna=True))
    data[col] = data[col].replace(np.NaN,mean)
```

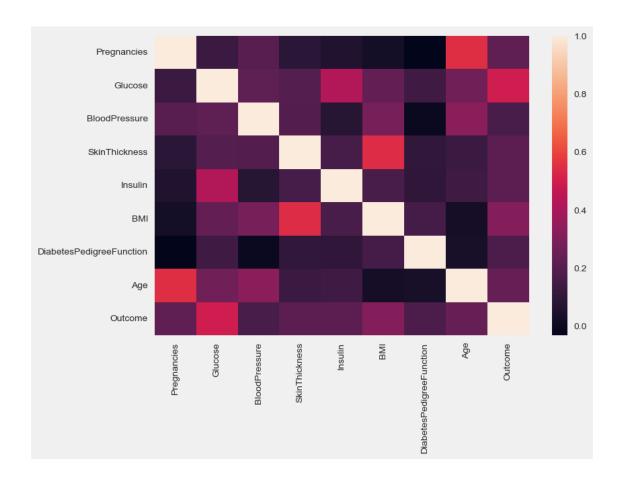
```
[107]: X = data.iloc[:,0:8]

[108]: y = data.iloc[:,8]
```

6.1 Explorning data to know relation before processing

```
[109]: sns.heatmap(data.corr())
```

[109]: <Axes: >



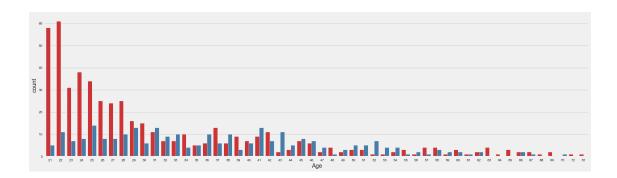
```
[110]: plt.figure(figsize=(25,7))
sns.countplot(x='Age',hue='Outcome',data=data,palette='Set1')
```

```
AttributeError
                                           Traceback (most recent call last)
Cell In[110], line 2
      1 plt.figure(figsize=(25,7))
---> 2 sns.countplot(x='Age',hue='Outcome',data=data,palette='Set1')
File ~\anaconda3\Lib\site-packages\seaborn\categorical.py:2955, in_
 \hookrightarrowcountplot(data, x, y, hue, order, hue_order, orient, color, palette, \sqcup
 ⇒saturation, width, dodge, ax, **kwargs)
   2952 if ax is None:
            ax = plt.gca()
   2953
-> 2955 plotter.plot(ax, kwargs)
   2956 return ax
File ~\anaconda3\Lib\site-packages\seaborn\categorical.py:1587, in _BarPlotter.
 →plot(self, ax, bar_kws)
   1585 """Make the plot."""
```

```
1586 self.draw_bars(ax, bar_kws)
-> 1587 self.annotate_axes(ax)
   1588 if self.orient == "h":
   1589
            ax.invert yaxis()
File ~\anaconda3\Lib\site-packages\seaborn\categorical.py:767, in_
 → CategoricalPlotter.annotate axes(self, ax)
            ax.set_ylim(-.5, len(self.plot_data) - .5, auto=None)
    766 if self.hue names is not None:
            ax.legend(loc="best", title=self.hue_title)
--> 767
File ~\anaconda3\Lib\site-packages\matplotlib\axes\_axes.py:322, in Axes.
 →legend(self, *args, **kwargs)
    204 @ docstring.dedent interpd
    205 def legend(self, *args, **kwargs):
    206
    207
            Place a legend on the Axes.
    208
   (...)
            .. plot:: gallery/text_labels_and_annotations/legend.py
    320
    321
--> 322
            handles, labels, kwargs = mlegend. parse legend args([self], *args,
 →**kwargs)
    323
            self.legend_ = mlegend.Legend(self, handles, labels, **kwargs)
    324
            self.legend_._remove_method = self._remove_legend
File ~\anaconda3\Lib\site-packages\matplotlib\legend.py:1361, in_
 → parse_legend_args(axs, handles, labels, *args, **kwargs)
            handles = [handle for handle, label
   1357
                       in zip(_get_legend_handles(axs, handlers), labels)]
   1358
   1360 elif len(args) == 0: # 0 args: automatically detect labels and handles
-> 1361
            handles, labels = _get_legend_handles_labels(axs, handlers)
            if not handles:
   1362
   1363
                log.warning(
                    "No artists with labels found to put in legend. Note that
   1364
                    "artists whose label start with an underscore are ignored "
   1365
                    "when legend() is called with no argument.")
   1366
File ~\anaconda3\Lib\site-packages\matplotlib\legend.py:1291, in_

    get_legend_handles_labels(axs, legend_handler_map)

   1289 for handle in _get_legend_handles(axs, legend_handler_map):
            label = handle.get_label()
   1290
-> 1291
            if label and not label.startswith('_'):
                handles.append(handle)
   1292
   1293
                labels.append(label)
AttributeError: 'numpy.int64' object has no attribute 'startswith'
```



```
[111]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
        →2,random_state=0)
[112]: scaler = StandardScaler()
       X_train = scaler.fit_transform(X_train)
       X_test = scaler.transform(X_test)
[113]: classifier = KNeighborsClassifier(n_neighbors=11,p=2,metric='euclidean')
[114]: classifier.fit(X_train,y_train)
[114]: KNeighborsClassifier(metric='euclidean', n_neighbors=11)
[115]: | y_pred = classifier.predict(X_test)
[116]: conf_matrix = confusion_matrix(y_test,y_pred)
       print(conf_matrix)
       print(f1_score(y_test,y_pred))
      [[94 13]
       [15 32]]
      0.6956521739130436
[117]: print(accuracy_score(y_test,y_pred))
      0.81818181818182
  []:
```