Used Vehicles Analysis and Price Prediction

- About the data set:
  - This data set is used vehicles data publically available on https://www.kaggle.com/datasets/austinreese/craigslist-carstrucks-data
- Description of data variables:
  - 'year': model year of a vehicle | int32
  - 'manufacturer': maker of a vehicle | categorical
  - 'cylinder': cylinder size of a vehicle | categorical
  - 'type': body type of a vehicle | categorical
  - 'paint_color': color of a vehicle | categorical
  - 'region': region where the vehicle was listed | categorical
  - 'state': state where the vehicle was listed | categorical
  - 'price': listing price on Craigslist.org | float
- In descriptic analysis, I explore which feature group(s) of vehicles have greater impact on listing prices, then followed with a correlation analysis of numerical varialbes(including converted categorical variable to numeric variable).
- In inferential analysis, I use the linear regression machine learning method to build five models, selecting the most accurate one to predict the price of used vehicles as desired.

Part 1: Import necessary libraries, load data, and check data types and structures

In [20]:
```
# Import necessary libraries:
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

```python
import pandas as pd
import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.formula.api import ols
```

In [21]:
```python
# Load dataset:
df = pd.read_csv('vehicles.csv', header=0)

# remove white space from cell and header
df = df.apply(lambda x: x.astype(str).str.strip() if x.dtype == "object" else x)
df.columns=df.columns.str.strip()
```

In [22]:
```python
# check column names, data types, total observations:
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 426880 entries, 0 to 426879
Data columns (total 26 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   id            426880 non-null  int64  
 1   url           426880 non-null  object 
 2   region        426880 non-null  object 
 3   region_url    426880 non-null  object 
 4   price         426880 non-null  int64  
 5   year          425675 non-null  float64
 6   manufacturer  426880 non-null  object 
 7   model         426880 non-null  object 
 8   condition     426880 non-null  object 
 9   cylinders     426880 non-null  object 
 10  fuel          426880 non-null  object 
 11  odometer      422480 non-null  float64
 12  title_status  426880 non-null  object 
 13  transmission  426880 non-null  object 
 14  VIN           426880 non-null  object 
 15  drive         426880 non-null  object 
 16  size          426880 non-null  object 
 17  type          426880 non-null  object 
 18  paint_color   426880 non-null  object 
 19  image_url     426880 non-null  object 
 20  description   426880 non-null  object 
 21  county        0 non-null       float64
 22  state         426880 non-null  object 
 23  lat           420331 non-null  float64
 24  long          420331 non-null  float64
 25  posting_date  426880 non-null  object 
dtypes: float64(5), int64(2), object(19)
memory usage: 84.7+ MB
```

In [127…

```
# A list of vehicles' model year for sale:
df.year.unique()
```

Out[127…

```
array([  nan, 2014., 2010., 2020., 2017., 2013., 2012., 2016., 2019.,
       2011., 1992., 2018., 2004., 2015., 2001., 2006., 1968., 2003.,
       2008., 2007., 2005., 1966., 2009., 1998., 2002., 1999., 2021.,
       1997., 1976., 1969., 1995., 1978., 1954., 1979., 1970., 1974.,
       1996., 1987., 2000., 1955., 1960., 1991., 1972., 1988., 1994.,
       1929., 1984., 1986., 1989., 1973., 1946., 1933., 1958., 1937.,
       1985., 1957., 1953., 1942., 1963., 1977., 1993., 1903., 1990.,
       1965., 1982., 1948., 1983., 1936., 1932., 1951., 1931., 1980.,
       1967., 1971., 1947., 1981., 1926., 1962., 1975., 1964., 1934.,
       1952., 1940., 1959., 1950., 1930., 1956., 1922., 1928., 2022.,
       1901., 1941., 1924., 1927., 1939., 1923., 1949., 1961., 1935.,
       1918., 1900., 1938., 1913., 1916., 1943., 1925., 1921., 1915.,
       1945., 1902., 1905., 1920., 1944., 1910., 1909.])
```

In [129…

```
# check null values:
df.isna().sum()
```

Out[129...

```
id                   0
url                  0
region               0
region_url           0
price                0
year              1205
manufacturer         0
model                0
condition            0
cylinders            0
fuel                 0
odometer          4400
title_status         0
transmission         0
VIN                  0
drive                0
size                 0
type                 0
paint_color          0
image_url            0
description          0
county          426880
state                0
lat               6549
long              6549
posting_date         0
dtype: int64
```

Part 2: Preprocess the data

In [131...

```
# Drop columns that won't be useful for this analysis:
df.drop(columns =['id','url','region_url','model','condition','VIN','image_url','county','transmission','title_status
```

In [132...

```
# Remove rows that impact accuracy of the analysis:
df= df[(df.price >= 2000) & (df.price <=500000) & (df.year >=1970)& (df.year < 2022) &(df.odometer<300000) & (df.odor
```

In [133...

```
# Remove null values in the cells:
df=df.dropna(subset=['lat','long','drive','lat','long'])
```

In [152…

```
# Remove 'nan' strings in those cells:
df=df[(df.year!='nan')&(df.price !='nan')&(df.manufacturer !='nan')&(df.cylinders !='nan')&(df.fuel !='nan')&(df.odor

# Recheck total observations:
df.shape
```

Out[152…

```
(137469, 13)
```

In [154…

```
# Change data type for year column:
df.year=df.year.astype(int)
```

Part 3: Descriptive statistics analysis

In [157…

```
# re-check data structure and data types:
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 137469 entries, 31 to 426878
Data columns (total 13 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   region        137469 non-null  object 
 1   price         137469 non-null  int64  
 2   year          137469 non-null  int32  
 3   manufacturer  137469 non-null  object 
 4   cylinders     137469 non-null  object 
 5   fuel          137469 non-null  object 
 6   odometer      137469 non-null  float64
 7   drive         137469 non-null  object 
 8   type          137469 non-null  object 
 9   paint_color   137469 non-null  object 
 10  state         137469 non-null  object 
 11  lat           137469 non-null  float64
 12  long          137469 non-null  float64
dtypes: float64(3), int32(1), int64(1), object(8)
memory usage: 14.2+ MB
```

In [159…

```
# Re-check missing values:
df.isnull().sum()
```

Out[159…

```
region          0
price           0
year            0
manufacturer    0
cylinders       0
fuel            0
odometer        0
drive           0
type            0
paint_color     0
state           0
lat             0
long            0
dtype: int64
```

In [161…

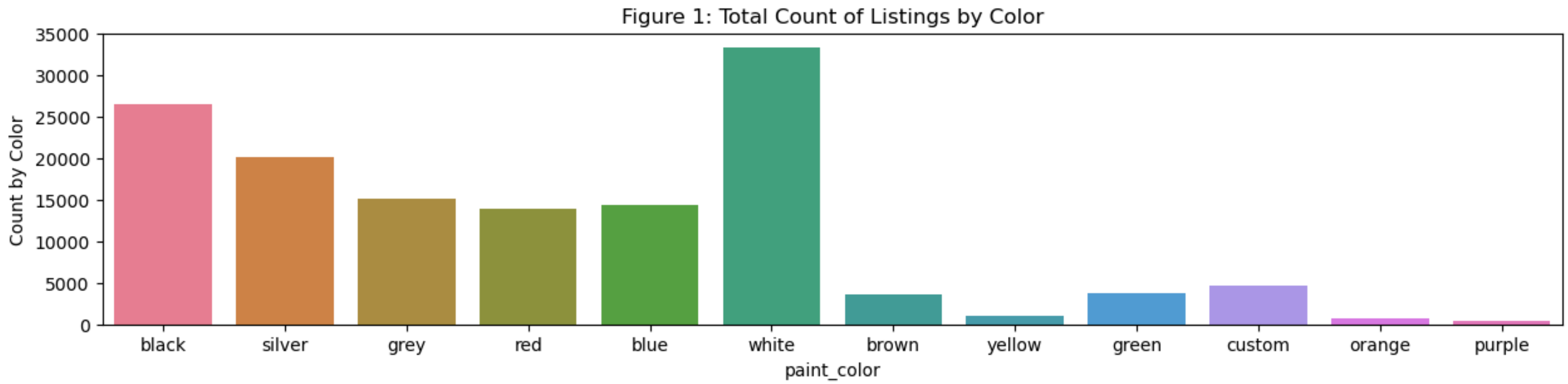
```
# re-check statistical summary:
df.describe()
```

Out[161…

	price	year	odometer	lat	long
count	137469.000000	137469.000000	137469.000000	137469.000000	137469.000000
mean	17773.750198	2011.044701	101588.451171	38.634585	-94.335534
std	13732.483014	7.051118	59477.895554	5.984344	18.450910
min	2000.000000	1970.000000	501.000000	-81.838232	-159.719900
25%	7400.000000	2008.000000	53000.000000	34.969253	-110.801411
50%	13800.000000	2013.000000	99095.000000	39.444084	-88.105874
75%	25590.000000	2016.000000	142000.000000	42.402459	-80.406800
max	289995.000000	2021.000000	299999.000000	82.252826	139.691700

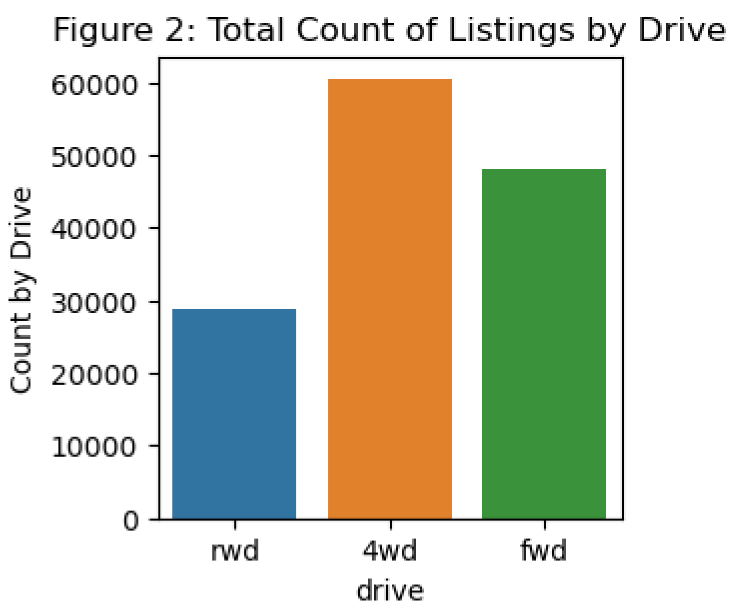
In [163…

```
# count by color group:
plt.figure(figsize=(15,3))
sns.countplot(data=df, x='paint_color', hue='paint_color')
plt.title('Figure 1: Total Count of Listings by Color')
plt.ylabel('Count by Color')
plt.show()
```



In [274…

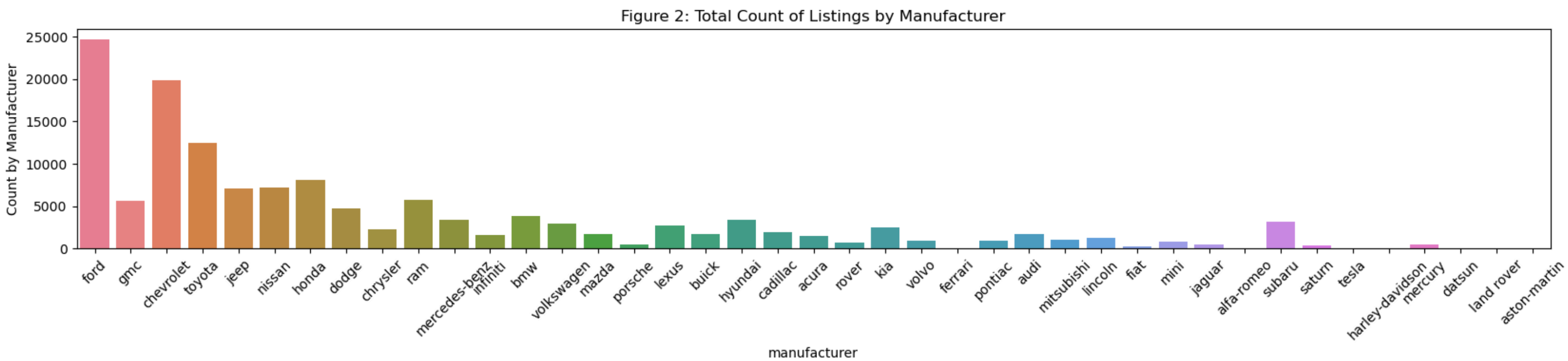
```
# count by drive group:
plt.figure(figsize=(3,3))
sns.countplot(data=df, x='drive', hue='drive')
plt.title('Figure 2: Total Count of Listings by Drive')
plt.ylabel('Count by Drive')
plt.show()
```



In [167…

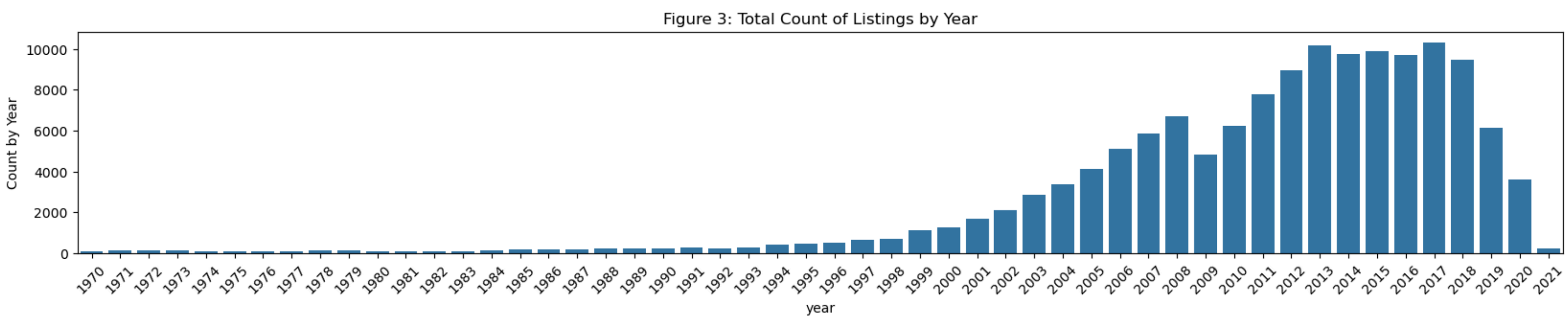
```
# count by manufacturer group:
plt.figure(figsize=(20,3))
```

```
sns.countplot(data=df, x='manufacturer', hue='manufacturer')
plt.title('Figure 2: Total Count of Listings by Manufacturer')
plt.ylabel('Count by Manufacturer')
plt.xticks(rotation=45)
plt.show()
```



In [173…

```
# count by year group:
plt.figure(figsize=(20,3))
sns.countplot(data=df, x='year')
plt.title('Figure 3: Total Count of Listings by Year')
plt.ylabel('Count by Year')
plt.xticks(rotation=45)
plt.show()
```



In [175…

```
# save the file to a csv file after cleaning for further visulization analysis using Tableau:
df.to_csv('vehicles_clean.csv', index= False)
```

Part 3 conclusions:

- White color of vehicle has the most number of listings, 4wd - Four wheel drive is the most popular drive type, followed by fwd - front wheel drive)

Part 4: Correlation analysis

In order to find out whether there are correlations between price and other non-numerical variables such as drive, color, cylinders, we will need to replace categorical name to numurical numbers for the pupose of correlation analysis.

- To replace categorical names to numerical numbers, for example:

```
drive['rwd', '4wd','fwd'] -- replaced with -- drive_n [1, 3, 2]
```

In [180…

```
dfn=pd.read_csv('vehicles_clean.csv', header=0)
```

In [182…

```
dfn
```

Out[182…

	region	price	year	manufacturer	cylinders	fuel	odometer	drive	type	paint_color	state	lat	lon
0	auburn	15000	2013	ford	6 cylinders	gas	128000.0	rwd	truck	black	al	32.592000	-85.5189(
1	auburn	27990	2012	gmc	8 cylinders	gas	68696.0	4wd	pickup	black	al	32.590000	-85.4800(
2	auburn	34590	2016	chevrolet	6 cylinders	gas	29499.0	4wd	pickup	silver	al	32.590000	-85.4800(
3	auburn	35000	2019	toyota	6 cylinders	gas	43000.0	4wd	truck	grey	al	32.601300	-85.44397
4	auburn	29990	2016	chevrolet	6 cylinders	gas	17302.0	4wd	pickup	red	al	32.590000	-85.4800(
...	...	...	...	...	...	...	...	...	...	...	...	...	
137464	wyoming	48590	2020	cadillac	6 cylinders	gas	7701.0	fwd	other	black	wy	33.779214	-84.41181
137465	wyoming	39990	2017	infiniti	8 cylinders	gas	41664.0	4wd	other	black	wy	33.779214	-84.41181
137466	wyoming	32990	2016	infiniti	8 cylinders	gas	55612.0	rwd	other	black	wy	33.779214	-84.41181
137467	wyoming	33590	2018	lexus	6 cylinders	gas	30814.0	rwd	sedan	white	wy	33.779214	-84.41181
137468	wyoming	28990	2018	lexus	6 cylinders	gas	30112.0	fwd	sedan	silver	wy	33.786500	-84.4454(

137469 rows × 13 columns

In [184…

```
dfn.dtypes
```

Out[184…

```
region          object
price            int64
year             int64
manufacturer    object
cylinders       object
fuel            object
odometer       float64
drive           object
type            object
paint_color     object
state           object
lat            float64
long           float64
dtype: object
```

In [186…

```
dfn.describe()
```

Out[186…

	price	year	odometer	lat	long
count	137469.000000	137469.000000	137469.000000	137469.000000	137469.000000
mean	17773.750198	2011.044701	101588.451171	38.634585	-94.335534
std	13732.483014	7.051118	59477.895554	5.984344	18.450910
min	2000.000000	1970.000000	501.000000	-81.838232	-159.719900
25%	7400.000000	2008.000000	53000.000000	34.969253	-110.801411
50%	13800.000000	2013.000000	99095.000000	39.444084	-88.105874
75%	25590.000000	2016.000000	142000.000000	42.402459	-80.406800
max	289995.000000	2021.000000	299999.000000	82.252826	139.691700

In [244…

```
# Remove string from column cylinders:
dfn['cylinders'] = dfn['cylinders'].astype(str)
dfn['cylinders'] = dfn['cylinders'].str.replace(' cylinders', '', regex=False)
dfn['cylinders'] = dfn['cylinders'].str.replace('other', '13', regex=False)
dfn['cylinders'] = dfn['cylinders'].astype(int)
dfn.cylinders.unique()
```

Out[244… array([6, 8, 4, 5, 10, 3, 13, 12])

In [256…
```
# add a column age, calculate the age of the vehicle by substracting model year from current year when the data was c
dfn['age'] = 2022 - dfn['year']
dfn.age.unique()
```

Out[256…
```
array([ 9, 10,  6,  3, 11,  5,  4, 18, 21,  8, 19, 14, 15,  2, 16, 17, 12,
       13, 20, 27, 48, 26, 22, 23,  7, 25, 24, 50,  1, 28, 43, 38, 46, 31,
       29, 32, 44, 40, 36, 34, 37, 33, 41, 30, 49, 47, 51, 35, 42, 45, 52,
       39], dtype=int64)
```

In [258…
```
# Ensure 'drive' is a string column:
dfn['drive'] = dfn['drive'].astype(str)

# Replace the values using a dictionary:
dfn['drive'] = dfn['drive'].replace({'rwd': '1', '4wd': '3', 'fwd': '2'})

# Convert 'drive' back to integer:
dfn['drive'] = dfn['drive'].astype(int)

# Check the unique values in the 'drive' column:
print(dfn['drive'].unique())
```

```
[1 3 2]
```

In [260…
```
dfn=dfn.dropna()
```

In [262…
```
dfn.to_csv('clean.csv')
```

EDA

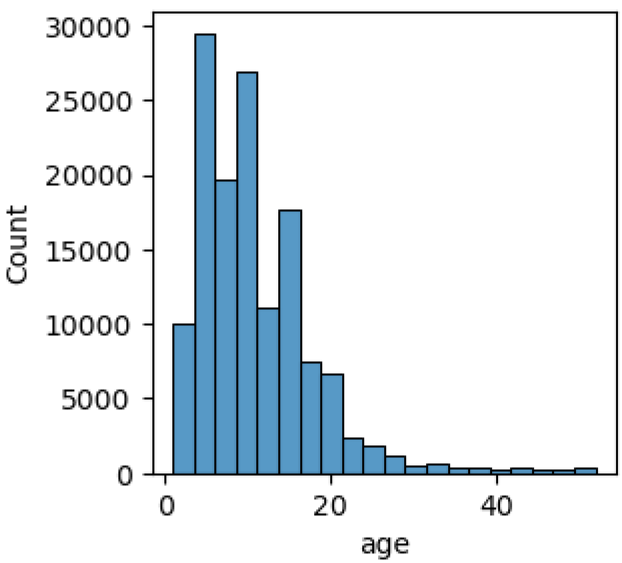
In [264…
```
dfn.head()
```

Out[264...

	region	price	year	manufacturer	cylinders	fuel	odometer	drive	type	paint_color	state	lat	long	age
0	auburn	15000	2013	ford	6	gas	128000.0	1	truck	black	al	32.5920	-85.518900	9
1	auburn	27990	2012	gmc	8	gas	68696.0	3	pickup	black	al	32.5900	-85.480000	10
2	auburn	34590	2016	chevrolet	6	gas	29499.0	3	pickup	silver	al	32.5900	-85.480000	6
3	auburn	35000	2019	toyota	6	gas	43000.0	3	truck	grey	al	32.6013	-85.443974	3
4	auburn	29990	2016	chevrolet	6	gas	17302.0	3	pickup	red	al	32.5900	-85.480000	6

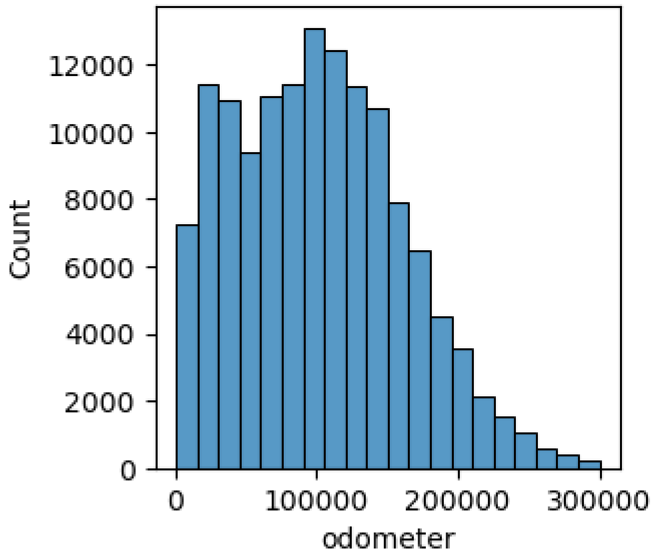
In [270...

```
plt.figure(figsize=(3, 3))
sns.histplot(dfn['age'], kde=False, bins=20)
# Show the plot
plt.show()
```



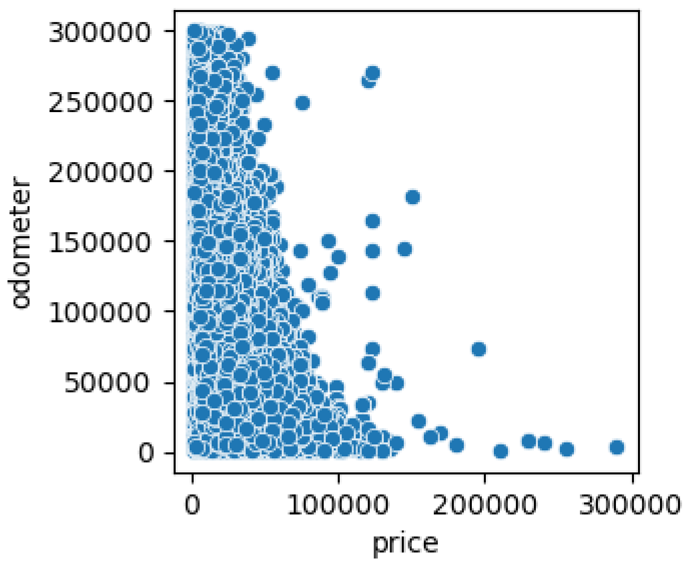
In [272...

```
plt.figure(figsize=(3, 3))
sns.histplot(dfn['odometer'], kde=False, bins=20)
plt.show()
```



In [240…

```
sns.scatterplot(data=dfn, x='price',y='odometer')
plt.show()
plt.figure(figsize=(3,3))
```

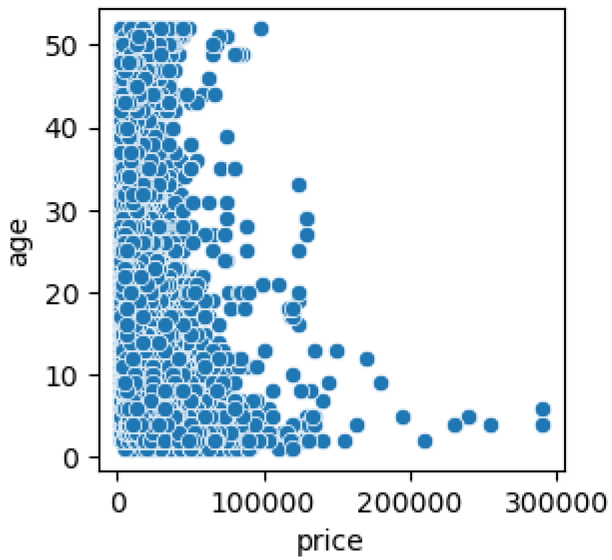


Out[240…

```
<Figure size 300x300 with 0 Axes>
```

In [242…

```
sns.scatterplot(data=dfn, x='price',y='age')
plt.show()
plt.figure(figsize=(3,3))
```

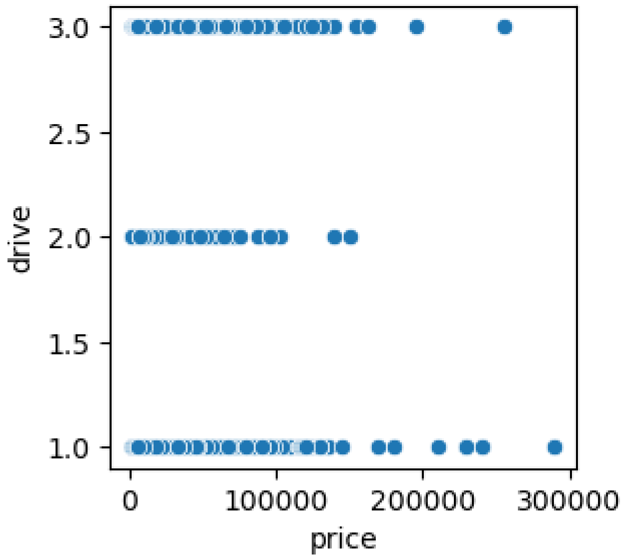


Out[242…

```
<Figure size 300x300 with 0 Axes>
```

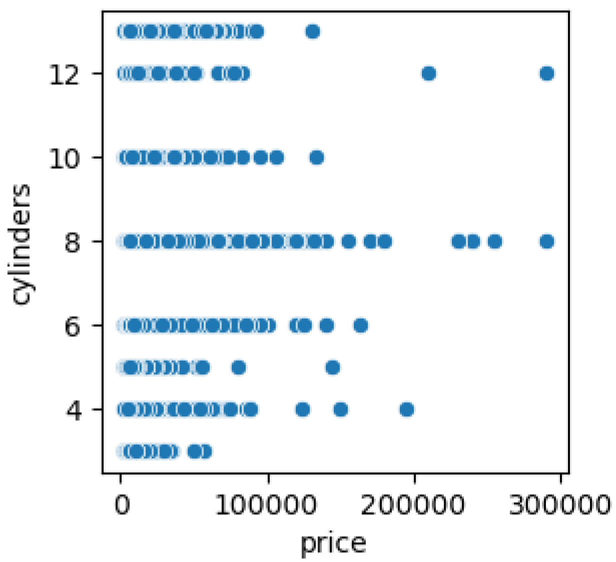
In [209…

```
sns.scatterplot(data=dfn, x='price',y='drive')
plt.show()
plt.figure(figsize=(3,3))
```



Out[209… <Figure size 300x300 with 0 Axes>

In [211…
```
sns.scatterplot(data=dfn, x='price',y='cylinders')
plt.show()
plt.figure(figsize=(3,3))
```



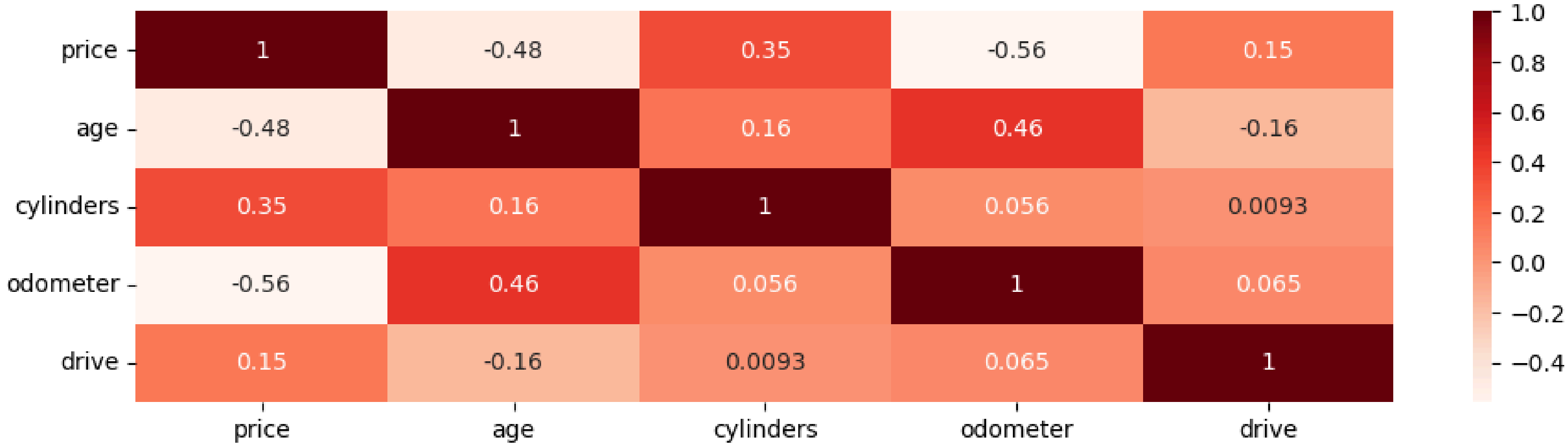
Out[211… <Figure size 300x300 with 0 Axes>

It seems like there is some negative relationship between price and odometer and age. let's use heatmap to show the strength of the relationship.

In [214…

```
# Create a heatmap to visulize the correlations:
corr = dfn[['price','age','cylinders','odometer','drive']]
plt.figure(figsize=(12,3))
sns.heatmap(corr.corr(), annot=True, cmap='Reds')
#plt.title('Figure 4: Correlation Heatmap')
plt.show()
```

<Figure size 300x300 with 0 Axes>



Part 4 Conclusion:

- Correlation analysis suggested:
    - a negative linear relationship between price(the dependent variable) and the explanatory variables: odometer, age.
    - a positive linear relationship between price and cylinders and drive.

Part 5: Inferential analysis

In [218…

```
model1 = smf.ols("price ~ odometer", data=dfn).fit()

print(model1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.312
Model:                            OLS   Adj. R-squared:                  0.312
Method:                 Least Squares   F-statistic:                 6.237e+04
Date:                Sun, 23 Feb 2025   Prob (F-statistic):               0.00
Time:                        10:14:53   Log-Likelihood:            -1.4791e+06
No. Observations:              137469   AIC:                         2.958e+06
Df Residuals:                  137467   BIC:                         2.958e+06
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   3.088e+04     60.800    507.849      0.000    3.08e+04     3.1e+04
odometer      -0.1290      0.001   -249.738      0.000      -0.130      -0.128
==============================================================================
Omnibus:                    71798.292   Durbin-Watson:                   1.542
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1456878.838
Skew:                           2.067   Prob(JB):                         0.00
Kurtosis:                      18.403   Cond. No.                     2.33e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.33e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [220…

```
model2 = smf.ols("price ~ age", data=dfn).fit()

print(model2.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                  price   R-squared:                       0.230
Model:                            OLS   Adj. R-squared:                  0.230
Method:                 Least Squares   F-statistic:                 4.103e+04
Date:                Sun, 23 Feb 2025   Prob (F-statistic):               0.00
Time:                        10:14:54   Log-Likelihood:            -1.4868e+06
No. Observations:              137469   AIC:                         2.974e+06
Df Residuals:                  137467   BIC:                         2.974e+06
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      2.8e+04     60.057    466.269      0.000    2.79e+04    2.81e+04
age         -933.7176      4.610   -202.552      0.000    -942.753    -924.683
==============================================================================
Omnibus:                    75568.150   Durbin-Watson:                   1.525
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1425392.091
Skew:                           2.246   Prob(JB):                         0.00
Kurtosis:                      18.122   Cond. No.                         24.2
==============================================================================

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

In [222…

```python
model3 = smf.ols('price ~ age + odometer', data=dfn).fit()

print(model3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.374
Model:                            OLS   Adj. R-squared:                  0.374
Method:                 Least Squares   F-statistic:                 4.111e+04
Date:                Sun, 23 Feb 2025   Prob (F-statistic):               0.00
Time:                        10:14:55   Log-Likelihood:            -1.4726e+06
No. Observations:              137469   AIC:                         2.945e+06
Df Residuals:                  137466   BIC:                         2.945e+06
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   3.383e+04     63.242    534.862      0.000    3.37e+04    3.39e+04
age         -547.6108      4.687   -116.842      0.000    -556.797    -538.425
odometer      -0.0990      0.001   -178.103      0.000      -0.100      -0.098
==============================================================================
Omnibus:                    79422.138   Durbin-Watson:                   1.540
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2119328.570
Skew:                           2.288   Prob(JB):                         0.00
Kurtosis:                      21.683   Cond. No.                     2.54e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.54e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [224…

```
model4 = smf.ols('price ~ age + odometer + cylinders', data=dfn).fit()

print(model4.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                  price   R-squared:                       0.553
Model:                            OLS   Adj. R-squared:                  0.553
Method:                 Least Squares   F-statistic:                 5.673e+04
Date:                Sun, 23 Feb 2025   Prob (F-statistic):               0.00
Time:                        10:14:56   Log-Likelihood:            -1.4494e+06
No. Observations:              137469   AIC:                         2.899e+06
Df Residuals:                  137465   BIC:                         2.899e+06
Df Model:                           3                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   1.415e+04     99.428    142.363      0.000     1.4e+04    1.43e+04
age         -692.7431      4.008   -172.819      0.000    -700.600    -684.887
odometer      -0.0965      0.000   -205.526      0.000      -0.097      -0.096
cylinders   3534.9838     15.067    234.611      0.000    3505.452    3564.516
==============================================================================
Omnibus:                    94577.747   Durbin-Watson:                   1.673
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          5407315.890
Skew:                           2.691   Prob(JB):                         0.00
Kurtosis:                      33.250   Cond. No.                     4.77e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.77e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [226…

```
model5 = smf.ols('price ~ age + odometer + drive + cylinders', data=dfn).fit()

print(model5.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.568
Model:                            OLS   Adj. R-squared:                  0.568
Method:                 Least Squares   F-statistic:                 4.511e+04
Date:                Sun, 23 Feb 2025   Prob (F-statistic):               0.00
Time:                        10:14:56   Log-Likelihood:            -1.4472e+06
No. Observations:              137469   AIC:                         2.894e+06
Df Residuals:                  137464   BIC:                         2.894e+06
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   9361.4145    120.706     77.556      0.000    9124.833    9597.996
age         -632.4618      4.042   -156.462      0.000    -640.385    -624.539
odometer      -0.1016      0.000   -217.117      0.000      -0.103      -0.101
drive       2194.3326     32.381     67.767      0.000    2130.867    2257.798
cylinders   3494.2375     14.834    235.555      0.000    3465.163    3523.312
==============================================================================
Omnibus:                    97120.996   Durbin-Watson:                   1.680
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          6333982.669
Skew:                           2.763   Prob(JB):                         0.00
Kurtosis:                      35.792   Cond. No.                     5.93e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.93e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Part 5 Conclusions:

- r2 for 5 models:
  - model 1: 0.312
  - model 2: 0.230
  - model 3: 0.374
  - model 4: 0.553

    - model 5: 0.568
- Model 5 has a highest R squared value (0.568), meaning it can explain the dependence variable better compared to other models.

Concluding Remarks:

- Descriptive data analysis shows pupular features or market trends inlude: white color, four wheel drive, followed by front wheel drive. Ford is the most pupular brand.

- Correlation analysis suggested a weak positive correlation between price(dependent variable) and drive type(independent variable), a negative correlation between price(dependent variable) and age and odometer(independent variables).

- Inferential analysis suggested Model 5 (odometer + age + cylinders + drive) is the best model, with a R squared of 0.568, meaning the combination of odometer + age + cylinders + drive can explain 56.8% variance in the listings.

In [ ]:

```
```

In [ ]:

```
```