UCSanDiegoX: DSE200x

Python for Data Science : Analysis of the Craigslist Used Cars Dataset (Kaggle)

Samuel Quiroga

May-Aug 2020

Abstract

In this final project of the Python for Data Science Course, I will look at the Used Cars Dataset from Craigslist. The data is available on Kaggle and it consists of vehicles sale listings from the website Craigslist.com.

The purpose of the analysis was to perform a **decision tree regression model** on the dataset to predict the price variable. The best prediction model attained a **%75** prediction accuracy.

Motivation

Used or previously owned vehicles are a great economic alternative to new vehicles for people with financial disadvantages. Those people with lower incomes, or people who are concerned with the large depreciation of new vehicles could greatly benefit from a used vehicle that is priced fairly.

My goal with this analysis is to determine the fair market price of a used vehicle based on a large dataset of available vehicle listings. This could be a tool that could benefit someone who is looking to buy a used vehicle but is unsure of what the right price should be offered for such vehicle.

Dataset(s)

The dataset used in this analysis is the Used Car Dataset from Kaggle https://www.kaggle.com/austinreese/craigslist-carstrucks-data). It contains most relevant information that Craigslist provides on car sales including columns like price, condition, manufacturer, latitude/longitude, and 18 other categories

The raw dataset is a table of 539759 rows and 25 columns. It comes in a .csv files called “vehicles.csv” and has a size of 1.42 GB.

Data Preparation and Cleaning

The columns that contained less than 70% of actual data (vs NA) was removed first. Then any sort of variable not needed for this analysis was removed (id, url, location, etc.). Lastly, any sort of outliers were removed using percentile cut-offs. Only the listings for vehicles with years between 1999 to 2019 were kept since those were the most common listings and therefore had larger amounts of instances.

Research Question(s)

Can the price of a used vehicle be predicted from this dataset using a Decision Tree Regressor? Variables used for the prediction model are: drive, type, title_status, fuel, transmission, odometer, and year

Methods

The initial data cleaning involved the use of **Pandas** package to remove any outliers and columns that contained less than 70% of NA values. For data visualization, the main type of plot was a box-plots because it clearly identified the data distribution for categorical variables. When comparing price and odometer readings, a very useful plot was a joint histogram using hexagonal bins. The two visualization libraries were **Matplotlib** and **Searborn**.

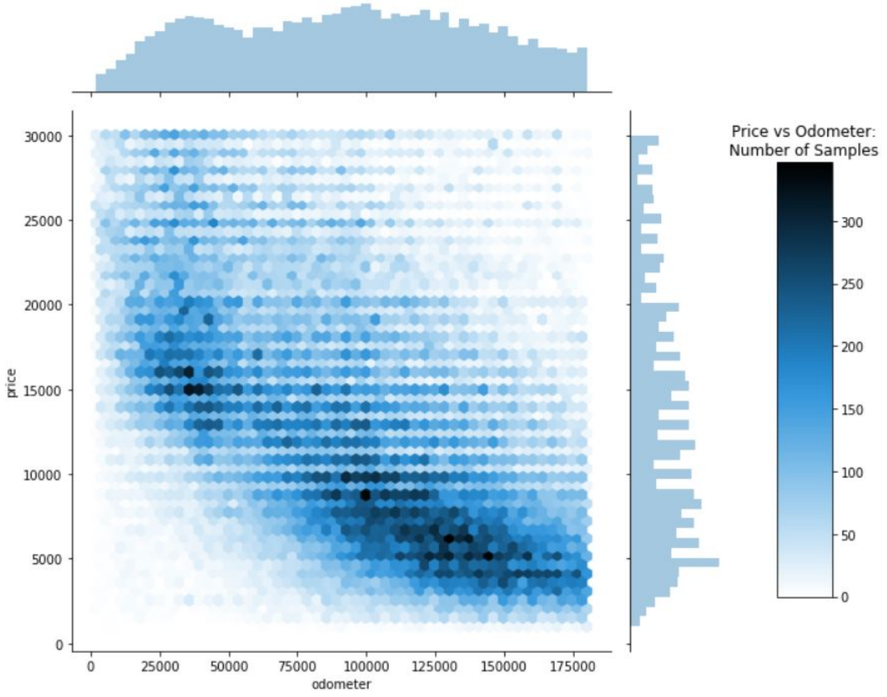
Findings : data cleaning

- Only columns that contained at least %70 of non-Null values were kept
- Outliers and non-NA values were removed from the dataset
- Variables used for the prediction model are: drive,type,title_status,fuel, transmission,odometer,year, and price
- Some categorical values were merged due to ambiguity (e.g. vehicle type 'truck' vs 'pickup')
- A sample of ten rows is displayed on the figure

	price	year	fuel	odometer	title_status	transmission	drive	type
326468	14995	2011.0	gas	130042.0	clean	automatic	4wd	SUV
13852	0	2013.0	gas	129200.0	clean	automatic	4wd	SUV
173796	1	2016.0	gas	47139.0	clean	other	4wd	truck
399223	22470	2016.0	gas	36717.0	clean	automatic	4wd	SUV
403954	21985	2017.0	gas	30016.0	clean	automatic	rwd	coupe
525205	18998	2013.0	gas	130923.0	clean	automatic	4wd	truck
274230	22900	2015.0	gas	77104.0	clean	other	4wd	pickup
235530	18600	2018.0	gas	18400.0	clean	other	fwd	other
489156	39700	2017.0	diesel	56774.0	clean	automatic	4wd	pickup
161041	4000	2006.0	gas	114700.0	clean	automatic	rwd	coupe

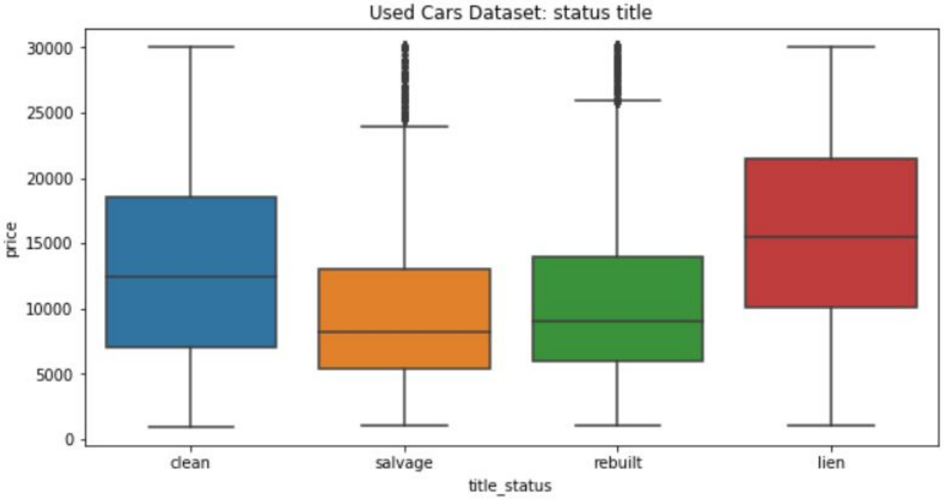
Findings : Price vs. Odometer Reading

A plot of a joint histogram using hexagonal bins of the price with odometer reading: notice the downward non-linear nature of of the data.



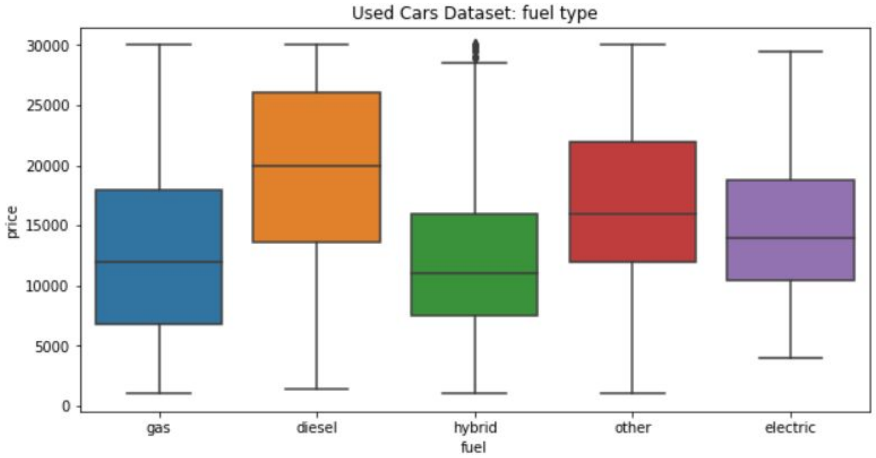
Findings: Title status distribution

A the boxplot of titles tatus vs price. Interestingly, vehicles with a lien tend to be higher priced. This could be because those vehicles typically are being sold to pay off creditors (banks, dealerships, etc.)



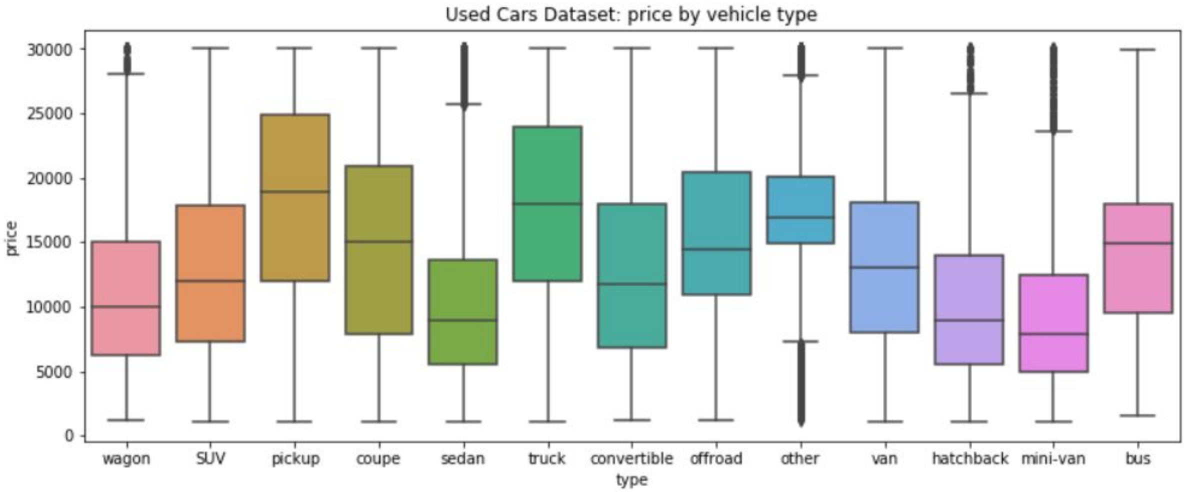
Findings: Fuel type distribution

A look at the distribution of prices by fuel type: notice that diesel-powered vehicles tend to be more expensive, while hybrid-types are the cheapest. Note, however, that diesel-powered vehicles could also be larger in general (Think trucks and SUV's), which makes them more expensive.



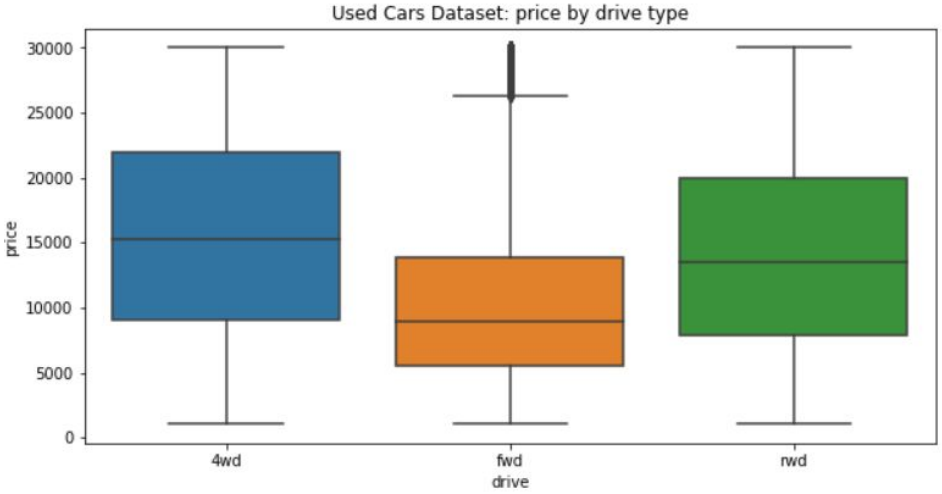
Findings: Vehicle type

There are quite a few types of vehicles in the data set. However, there are some types that do not occur very often ("bus", "off-road") and other types that could refer to the same vehicle type ("pickup" and "truck", which interestingly have very similar distributions, making it very possible that those are the same type).



Findings: Drive type

Now we'll look at the drive variable. In this case, there is a clear difference between all types and also have large number of instances, so there is no further cleaning be done in this case.



Findings: Decision Tree regressor

I first use the default parameters for the regressor function.

We see that our training accuracy is 98.8% but our testing accuracy is %73. This means that the model is overfitting the data. In order to mitigate this, I use Sklearn's Randomized Search Cross-Validation

```
# create a regressor object
regressor = DecisionTreeRegressor(random_state = 66)
regressor.fit(X_train, y_train)
```

```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='deprecated',
                      random_state=66, splitter='best')
```

```
y_predicted = regressor.predict(X_test)
print('Training accuracy: ',regressor.score(X_train,y_train))
print('Test Accuracy: ',regressor.score(X_test,y_test))
```

```
Training accuracy:  0.9878322641478163
Test Accuracy:  0.7326405511046303
```

Findings Decision Tree regressor

We can see that the randomized search cross-validation improved the model accuracy by ~2% for the best score to a total of 75.4%

```
param_grid = {"criterion": ["mse", "mae"],
              "min_samples_split": [10, 20, 40, 50, 60],
              "max_depth": [2, 6, 8, 12, 14],
              "min_samples_leaf": [10 ,20, 40, 100],
              }

n_iter_search = 10

rand_search_cv = RandomizedSearchCV(estimator=regressor,
                                    param_distributions= param_grid,
                                    cv=5,
                                    n_iter=n_iter_search,
                                    n_jobs=-1)
```

```
RandomizedSearchCV took 2359.94 seconds for 10 candidates parameter settings.
Model with rank: 1
Mean validation score: 0.754 (std: 0.002)
Parameters: {'min_samples_split': 50, 'min_samples_leaf': 20, 'max_depth': 14, 'criterion': 'mse'}

Model with rank: 2
Mean validation score: 0.753 (std: 0.001)
Parameters: {'min_samples_split': 20, 'min_samples_leaf': 20, 'max_depth': 12, 'criterion': 'mse'}

Model with rank: 3
Mean validation score: 0.751 (std: 0.002)
Parameters: {'min_samples_split': 40, 'min_samples_leaf': 40, 'max_depth': 14, 'criterion': 'mse'}
```

Limitations

- A large number of levels in the categorical variables were used in this dataset, which could have impacted the model performance by over-fitting it (hence the high test error rate).
- The location information (lat/long, state) was not used in this analysis but could have added more information.

Further Improvement

Some more work is required to improve the mode accuracy. A few things that could be done:

- Trying reducing the number of levels in the categorical variables.
- Exploring a simpler multi-linear model that only uses numerical data (price, odometer, and year).
- Exploring a more complex model, such as Random Forests to increase the level of accuracy.

Conclusions

In this final project of the Python for Data Science Course, I will look at the Used Cars Dataset from Craigslist. The data is available on Kaggle and it consists of vehicles sale listings from the website Craigslist.com.

The purpose of the analysis was to perform a **decision tree regression model** on the dataset to predict the price variable. The best prediction model attained a **%75** prediction accuracy.

Acknowledgements

The data was available on Kaggle:
https://www.kaggle.com/austinreese/craigslist-carstrucks-data

No feedback was provided

References

The package documentation for Scikit Learn, Pandas, and Searborn were very helpful on providing information and ideas for coding and visualiztion.

Tip on how to open zipfiles take from https://www.kaggle.com/mchirico/how-to-read-datasets

UCSanDiegoX: DSE200x

Python for Data Science : Analysis of The Used Cars Dataset (Kaggle)

Samuel Quiroga (April-August 2020)

Project Overview

In this final project of the Python for Data Science Course, I will look at the Used Cars Dataset from Craigslist. The data is available on *Kaggle* (link [here (https://www.kaggle.com/austinreese/craigslist-carstrucks-data%5D)](https://www.kaggle.com/austinreese/craigslist-carstrucks-data%5D)) and it consists of vehicles sale listings from the website Craigslist.com.

Research Question

Can the price of a vehicle be predicted from this dataset using a Decision Tree Regressor?

Executive Summary

The purpose of the analysis was to perform a **decision tree regression model** on the dataset to predict the `price` variable. Here is a summary of the steps involved:

- Only colums that contained at least %70 of non-Null values were kept
- Outliers and non-NA values were removed from the dataset
- Variables used for the prediction model are: `drive` , `type` , `title_status` , `fuel` , `transmission` , `odometer` , `year` , and `price`
- Some categorical values were merged due to ambiguity (e.g. `vehicle type` 'truck' vs 'pickup')
- Categorical variables were hot-encoded (0 and 1)
- Randomized Search Cross-Validation was performed on the regressor model to obtain a better fit but there was no significant improvement on the prediction accuracy
- The best prediction model attained a **%75** prediction accuracy with the following decision tree parameters:

  `Mean validation score: 0.755 (std: 0.002)`

  `Parameters: {'min_samples_split': 20, 'min_samples_leaf': 20, 'max_depth': 14, 'criterion': 'mse'}`

Analysis Limitations

There are some possible limitations to the analysis:

- A large number of levels in the categorical variables were used in this dataset, which could have impacted the model performance by over-fitting it (hense the high test error rate).
- The locaion information (lat/long, state) was not used in this analysis but could have added more information.

Further Improvement

Some more work is required to improve the mode accuracy. A few things that could be done:

- Trying reducing the number of levels in the categorical variables.
- Exploring a simpler multi-linear model that only uses numerical data (`price` , `odometer` , and `year`).
- Exploring a more complex model, such as Random Forests to increase the level of accuracy.

In [6]:
```
# import required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Load regression libraries
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.tree import DecisionTreeRegressor
```

Import and read dataset

First, look for the downloaded file from [https://www.kaggle.com/austinreese/craigslist-carstrucks-data/download (https://www.kaggle.com/austinreese/craigslist-carstrucks-data/download)](https://www.kaggle.com/austinreese/craigslist-carstrucks-data/download).

In [2]:
```
from subprocess import check_output
print(check_output(["ls", "./data"]).decode("utf8"))
```

```
craigslist-carstrucks-data.zip
```

Unzip the file and extract into the data folder.

In [3]:
```
# how to from https://www.kaggle.com/mchirico/how-to-read-datasets
import zipfile
Dataset = "craigslist-carstrucks-data"

with zipfile.ZipFile("./data/"+Dataset+".zip","r") as z:
     z.extractall("./data")
```

Import data as pandas dataframe.

In [7]:
```
cars_raw = pd.read_csv("./data/vehicles.csv")
```

In [5]:
```
# dataframe shape
print("Number of rows:",cars_raw.shape[0])
print()
print("Number of columns",cars_raw.shape[1])
```

```
Number of rows: 539759

Number of columns 25
```

Preliminary Data Cleaning

Remove unnecessary columns and null values. Let's look at the proportion of non-null values as percent of total number of rows. This will give us an idea of which variables contain the most amount of actual data vs those that are mostly `NULL` .

In [9]:
```python
no_null_prc = (cars_raw.count()/len(cars_raw)).round(2)*100
no_null_prc
```

Out[9]:
```
id              100.0
url             100.0
region          100.0
region_url      100.0
price           100.0
year            100.0
manufacturer     96.0
model            99.0
condition        56.0
cylinders        60.0
fuel             99.0
odometer         82.0
title_status     99.0
transmission     99.0
vin              58.0
drive            71.0
size             31.0
type             73.0
paint_color      68.0
image_url       100.0
description     100.0
county            0.0
state           100.0
lat              98.0
long             98.0
dtype: float64
```

Select columns of interest that have greater than 70% of actual data (no-NULL values).

In [10]:
```python
cols_to_use = list(no_null_prc[no_null_prc>=70].index)
cols_to_use
```

Out[10]:
```
['id',
 'url',
 'region',
 'region_url',
 'price',
 'year',
 'manufacturer',
 'model',
 'fuel',
 'odometer',
 'title_status',
 'transmission',
 'drive',
 'type',
 'image_url',
 'description',
 'state',
 'lat',
 'long']
```

Remove columns that will not be used further in the analysis: these columns only contain the `id` and other `url` information. We also remove `description` , `image_url` , and `location` information. We also remove the `model` and `manufacturer` columns.

In [11]:
```
cols_not_needed = list(cars_raw.columns[0:4])
cols_not_needed.extend(['description','image_url','state','lat','long','manufacturer','mode
cols_not_needed
```

Out[11]:
```
['id',
 'url',
 'region',
 'region_url',
 'description',
 'image_url',
 'state',
 'lat',
 'long',
 'manufacturer',
 'model']
```

Lastly, we remove any `na` values and select our features of interest

In [12]:
```
cars = cars_raw[[name for name in cols_to_use if name not in cols_not_needed]]
cars = cars.dropna()
cars.sample(10)
```

Out[12]:

	price	year	fuel	odometer	title_status	transmission	drive	type
326468	14995	2011.0	gas	130042.0	clean	automatic	4wd	SUV
13852	0	2013.0	gas	129200.0	clean	automatic	4wd	SUV
173796	1	2016.0	gas	47139.0	clean	other	4wd	truck
399223	22470	2016.0	gas	36717.0	clean	automatic	4wd	SUV
403954	21985	2017.0	gas	30016.0	clean	automatic	rwd	coupe
525205	18998	2013.0	gas	130923.0	clean	automatic	4wd	truck
274230	22900	2015.0	gas	77104.0	clean	other	4wd	pickup
235530	18600	2018.0	gas	18400.0	clean	other	fwd	other
489156	39700	2017.0	diesel	56774.0	clean	automatic	4wd	pickup
161041	4000	2006.0	gas	114700.0	clean	automatic	rwd	coupe

Description of the variables:

Here is a breakdown of the variables and their types.

Categorical variables:

- drive
- type
- fuel
- title_status
- transmission

Numerical variables:

- price
- odometer

Date variables:

- year

In [13]:
```
# dataframe shape
print("Number of rows:",cars.shape[0])
print()
print("Number of columns",cars.shape[1])
```

```
Number of rows: 302911

Number of columns 8
```

Preliminary data exploration and further cleaning

We will now explore the data and determine what further cleaning needs to be done. First, lets look at the distribution of the numeric variables, here is a summary of the median data :

- Median price is $10,990 while the max value is 4.2 billion dollars!
- Median odometer reading is 94674 mi.
- Median year is 2012

Here are some more additiona statistics.

In [14]:
```
cars.describe(percentiles=[0.05,0.1,0.5,0.9,0.95]).transpose()
```

Out[14]:

	count	mean	std	min	5%	10%	50%	90%	95%	
price	302911.0	191389.370987	2.333448e+07	0.0	0.0	900.0	10990.0	28000.0	34900.0	4.1982
year	302911.0	2010.844987	7.058727e+00	1900.0	2000.0	2003.0	2012.0	2017.0	2018.0	2.0210
odometer	302911.0	100539.526382	1.132707e+05	0.0	12933.0	23581.0	93674.0	179000.0	205000.0	1.0000

Price and Odometer

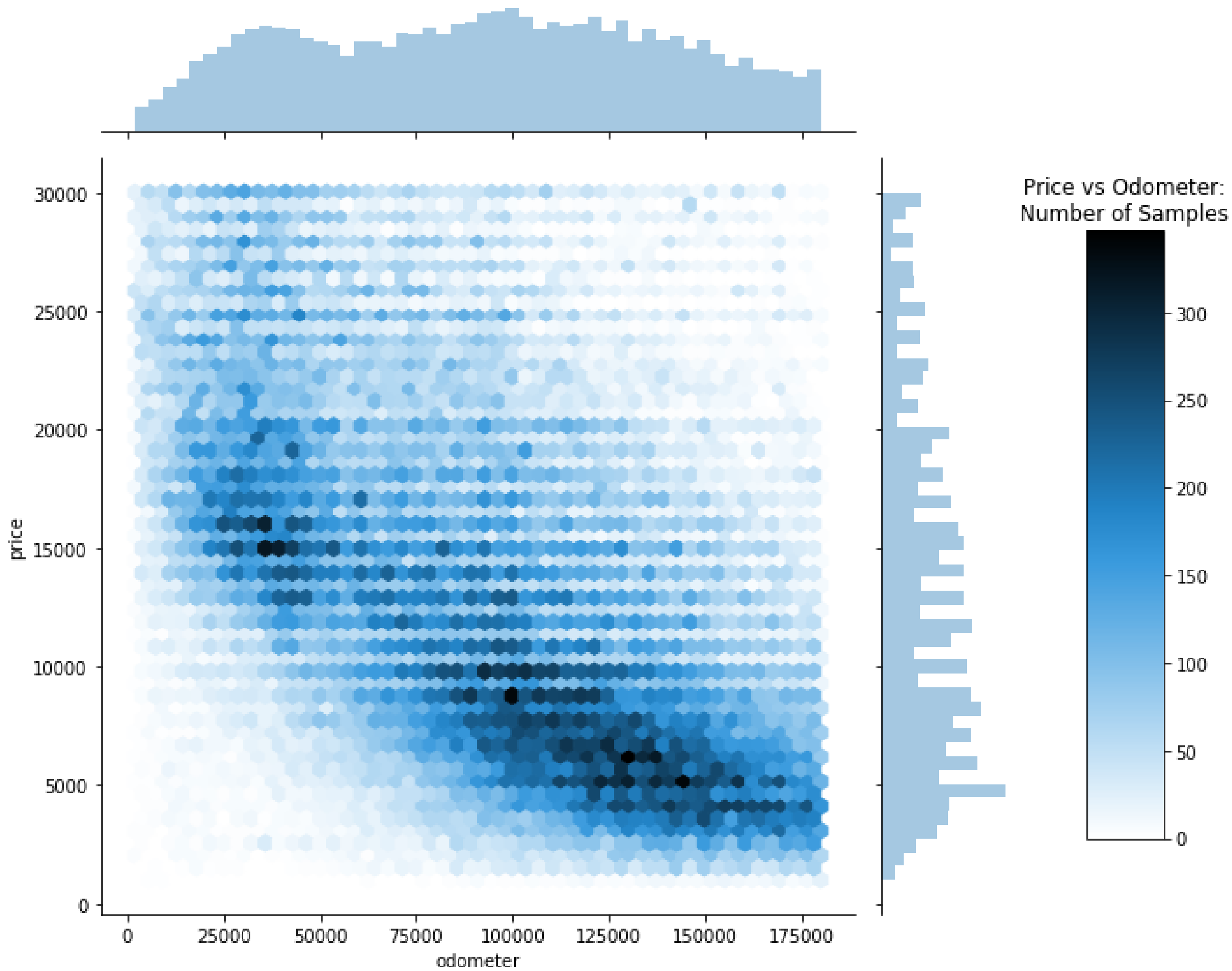
Remove vehicles with prices and odometer readings that are slightly more than the 90% percentile and less than the 1% percentile. This will get rid of extreme outliers. We will also remove `year` values equal to zero.

In [12]:
```
cars = cars[(cars.price<=30000) &
              (cars.price>1000) &
              (cars.odometer<=180000) &
              (cars.odometer>=2000) &
              (cars.year > 0)]

# dataframe shape
print("Number of rows:",cars.shape[0])
print()
print("Number of columns",cars.shape[1])
```

```
Number of rows: 217652

Number of columns 8
```

Let's look at a plot of a joint histogram using exagonal bins of the price with odometer reading: notice the downward non-linear nature of of the data.

In [13]:
```
# how to add legend from https://stackoverflow.com/questions/29096632/getting-legend-in-sea
hexplot = sns.jointplot("odometer", "price", data=cars,height=12,kind = "hex");
cbar_ax = hexplot.fig.add_axes([.85, .25, .05, .4])  # x, y, width, height
plt.subplots_adjust(left=0.2, right=0.8, top=0.8, bottom=0.2)  # shrink fig so cbar is visi
plt.colorbar(cax=cbar_ax)
plt.title('Price vs Odometer:\nNumber of Samples')
plt.show()
```



Transmission

Now let's look a the `transmission` type. A large majority of values in transmission are laballed as "other":

In [14]:
```
cars.transmission.value_counts()
```

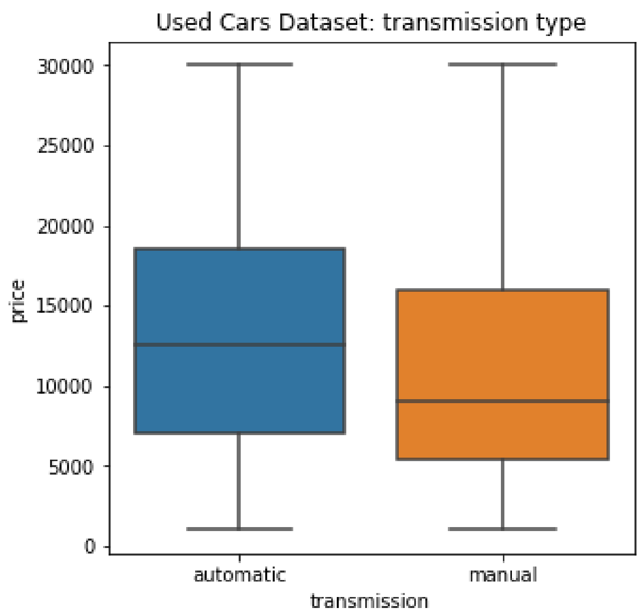
Out[14]:
```
automatic    192228
other         13120
manual        12304
Name: transmission, dtype: int64
```

We'll assume transmission labeled "other" is automatic:

```
In [15]: cars['transmission'] = np.where(cars.transmission == "other","automatic",cars.transmission)
```

Now let's look at the boxplot of transmission type vs price. Notice that vehicles with an automatic transmission tend to be at slightly higher price:

```
In [16]: plt.figure(figsize=(5,5))
         sns.boxplot(x='transmission',y='price',data=cars).set_title('Used Cars Dataset: transmissio
```



Title Status

A very small number of listings of `title_status` values are either labeled "missing" or "parts only". So we'll remove those variables from the dataset.

```
In [17]: cars.title_status.value_counts()
```

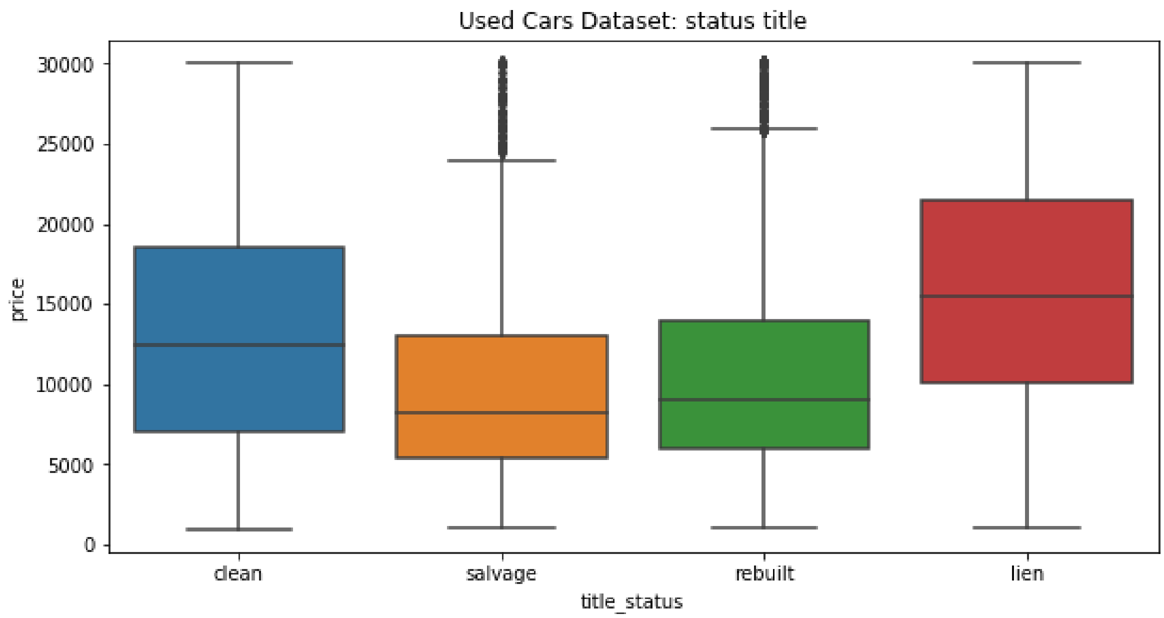
```
Out[17]: clean         207502
         rebuilt         6372
         salvage         2217
         lien            1455
         missing           85
         parts only        21
         Name: title_status, dtype: int64
```

```
In [18]: # remove 'missing' and 'parts only'
         keep = ['clean','rebuilt','salvage','lien']
         cars = cars[cars['title_status'].isin(keep)]
         # dataframe shape
         print("Number of rows:",cars.shape[0])
         print()
         print("Number of columns",cars.shape[1])
```

```
Number of rows: 217546

Number of columns 8
```

Now let's look a the boxplot of `titlestatus` vs `price`. Interestingly, vehicles with a lien tend to be higher priced. This could be because those vehicles typically are being sold to pay off creditors (banks, dealerships, etc.)

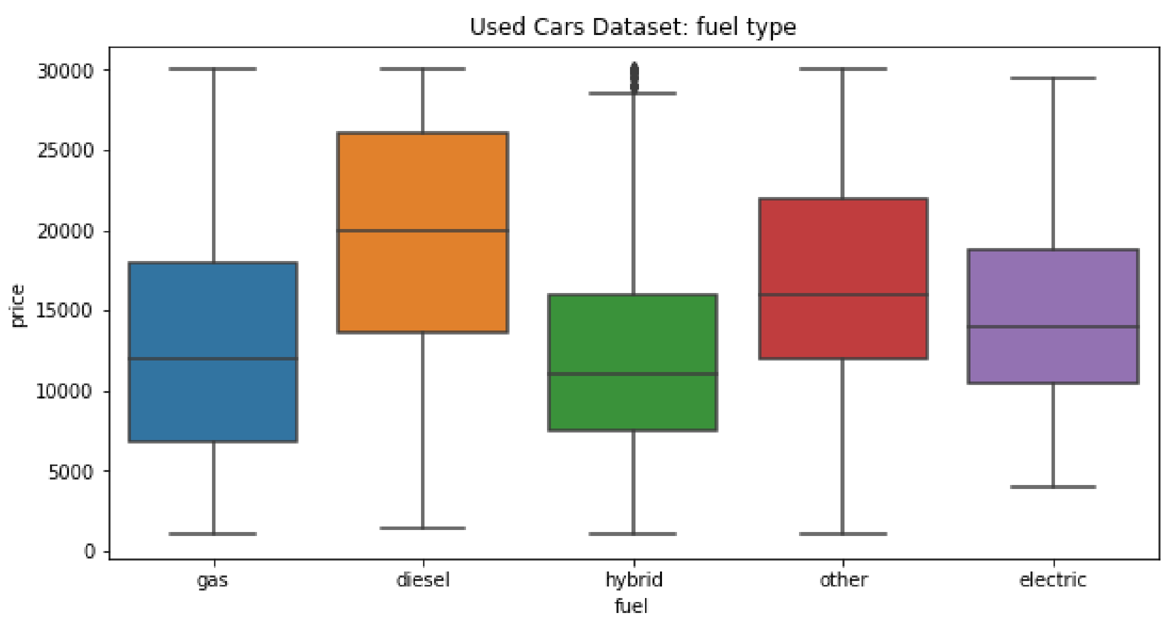
In [19]:
```
plt.figure(figsize=(10,5))
sns.boxplot(x='title_status',y='price',data=cars).set_title('Used Cars Dataset: status titl
```



Fuel Type

Let's take a look at the distribution of `prices` by `fuel` type: notice that diesel-powered vehicles tend to be more expensive, while hybrid-types are the cheapest. Note, however, that diesel-powered vehicles could also be larger in general (Think trucks and SUV's), which makes them more expensive.

In [20]:
```
plt.figure(figsize=(10,5))
sns.boxplot(x='fuel',y='price',data=cars).set_title('Used Cars Dataset: fuel type');
```



Vehicles with fuel type as "other" can be removed from the analysis since it would be difficult to identify the fuel type to for those vehicles:

In [21]:
```
cars.fuel.value_counts()
```

Out[21]:
```
gas         199815
diesel        9689
other         5315
hybrid        2268
electric       459
Name: fuel, dtype: int64
```

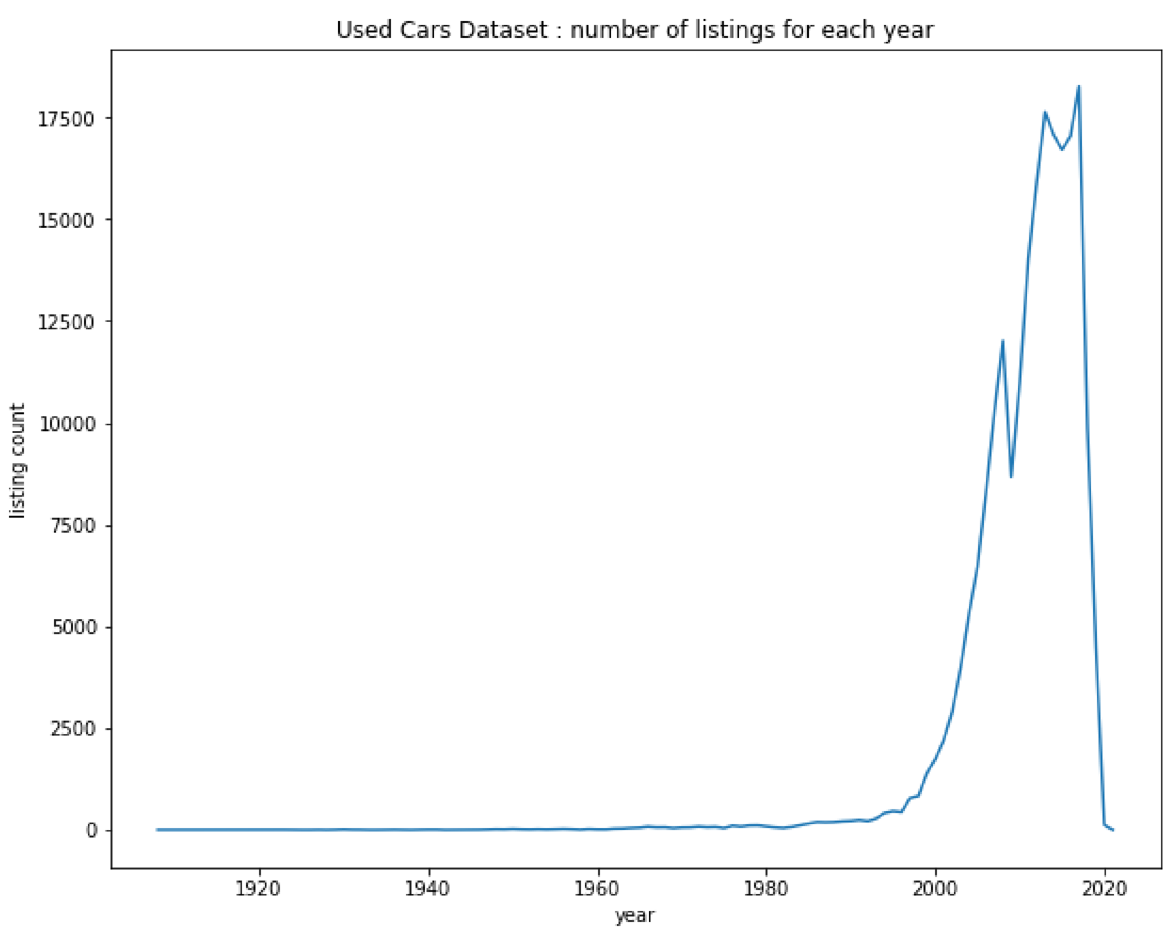
In [22]:
```
# remove fuel type "other"
cars = cars[~cars['fuel'].isin(['other'])]
# dataframe shape
print("Number of rows:",cars.shape[0])
print()
print("Number of columns",cars.shape[1])
```

```
Number of rows: 212231

Number of columns 8
```

Year

Lets see the number of vehicles grouped by `year` on a line plot: notice that most vehicles listings are for vehicles of years between the late 90's and early 2020.

In [23]:
```
grouped_by_year = cars.groupby('year').count().reset_index()
plt.figure(figsize=(10,8))
ax = sns.lineplot(x='year',y='price',data=grouped_by_year);
ax.set(ylabel="listing count",title='Used Cars Dataset : number of listings for each year')
```



For this analysis we'll look at listings between 1999 and 2019:

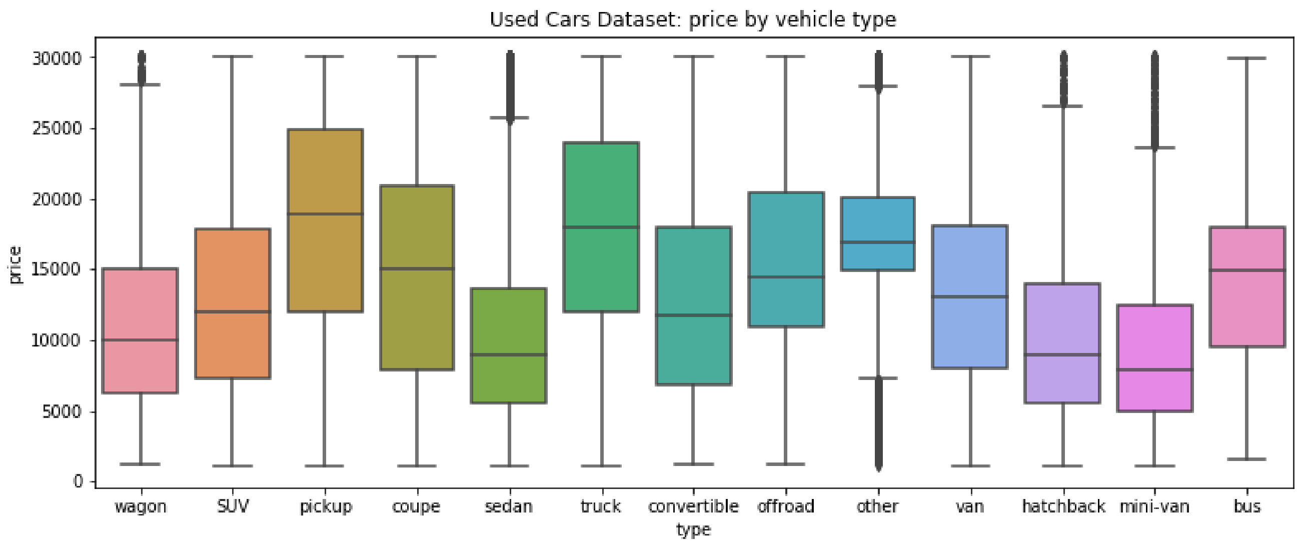
In [24]:
```
cars = cars[(cars.year>=1999) & (cars.year<=2019)]
# dataframe shape
print("Number of rows:",cars.shape[0])
print()
print("Number of columns",cars.shape[1])
```

```
Number of rows: 205263

Number of columns 8
```

Vehicle Type

Let's now look at vehicle type. There are quite a few types of vehicles in the data set. However, there are some types that do not occur very often ("bus", "off-road") and other types that could refer to the same vehicle type ("pickup" and "truck", which interestingly have very similar distributions, making it very possible that those are the same type).

In [25]:
```
plt.figure(figsize=(13,5))
sns.boxplot(x='type',y='price',data=cars).set_title('Used Cars Dataset: price by vehicle ty
```



In [26]:
```
cars.type.value_counts()
```

Out[26]:
```
sedan          57573
SUV            52793
truck          22989
pickup         22393
coupe          11464
hatchback       8727
other           7896
wagon           7390
van             5385
convertible     4342
mini-van        3828
offroad          310
bus              173
Name: type, dtype: int64
```

We can remove instances that do not occur very often (type `offroad` and `bus`), as well as `other` . Can also merge the `pickup` and `truck` categories into one: `pickup` .

In [27]:
```
# remove type "bus","offroad","other"
cars = cars[~cars['type'].isin(['other','offroad','bus'])]
# change "truck" to "pickup"
cars['type'] = np.where(cars.type == "truck","pickup",cars.type)
```

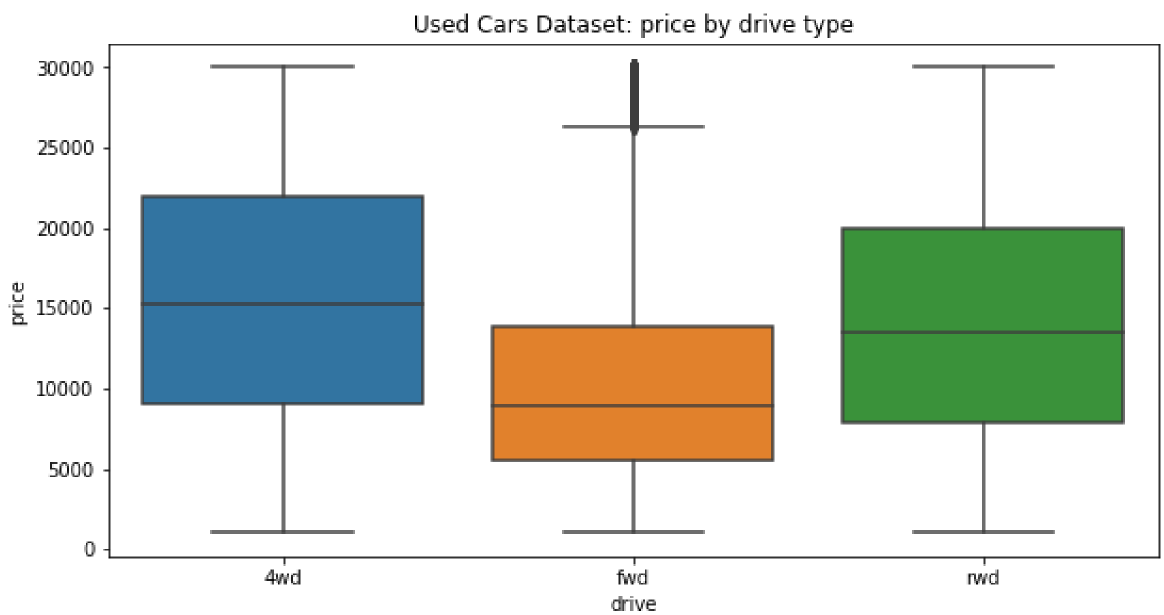
In [28]:
```
cars.type.value_counts()
```

Out[28]:
```
sedan          57573
SUV            52793
pickup         45382
coupe          11464
hatchback       8727
wagon           7390
van             5385
convertible     4342
mini-van        3828
Name: type, dtype: int64
```

Drive Type

Now we'll look at the `drive` variable. In this case, there is a clear difference between all types and also have large number of instances, so there is no further cleaning be done in this case.

In [29]:
```
plt.figure(figsize=(10,5))
sns.boxplot(x='drive',y='price',data=cars).set_title('Used Cars Dataset: price by drive typ
```



In [30]:
```
cars.drive.value_counts()
```

Out[30]:
```
4wd    83753
fwd    79820
rwd    33311
Name: drive, dtype: int64
```

Data Ready for Regression Excercise

Here is what the data looks like so far (take 10 samples):

In [31]:
```
cars.sample(10)
```

Out[31]:

	price	year	fuel	odometer	title_status	transmission	drive	type
47765	7000	2006.0	gas	152000.0	clean	automatic	4wd	pickup
363454	17995	1999.0	diesel	110295.0	clean	manual	rwd	pickup
505419	5495	2010.0	gas	150919.0	clean	automatic	rwd	wagon
120907	8995	2013.0	gas	107625.0	clean	automatic	fwd	sedan
30125	6500	2008.0	gas	139000.0	clean	automatic	rwd	coupe
390093	24999	2011.0	gas	39868.0	clean	manual	rwd	coupe
283787	8999	2007.0	gas	84573.0	clean	automatic	rwd	van
58132	18980	2014.0	gas	121596.0	clean	automatic	rwd	pickup
85288	10911	2011.0	gas	161464.0	clean	automatic	4wd	SUV
528769	5500	2010.0	gas	147792.0	clean	automatic	4wd	SUV

In [32]:
```
cars.shape
```

Out[32]: (196884, 8)

Decision Tree Regression

We are now ready to predict the `price` of a vehicle using a Decision Tree Regression. First we identify the predicted variable.

In [34]:
```
# predicted variable
y = cars[['price']].copy()
y.head()
```

Out[34]:

	price
5	12995
6	10995
10	7995
16	12995
17	12995

Now we extract the predictors (feature variables):

In [35]:
```
# features
X = cars.iloc[:,1:].copy()
X.head()
```

Out[35]:

	year	fuel	odometer	title_status	transmission	drive	type
5	2015.0	gas	85127.0	clean	automatic	4wd	wagon
6	2014.0	gas	112383.0	clean	automatic	fwd	SUV
10	2008.0	gas	162214.0	clean	automatic	fwd	pickup
16	2009.0	gas	146353.0	clean	automatic	4wd	SUV
17	2009.0	gas	146353.0	clean	automatic	4wd	SUV

Encode Categorical Variables

Since a Decision Tree Regressor requires numberic variables, we'll have to encode the categorical variables with `get_dummies` function from Pandas. This will make each variable either 0 or 1 at the expense of adding a large number of columns (since it will add a column or each category).

In [36]:
```
cat_columns = ['fuel','title_status','transmission','type','drive']
X_enc = pd.get_dummies(X,columns = cat_columns)
X_enc.sample(6)
```

Out[36]:

	year	odometer	fuel_diesel	fuel_electric	fuel_gas	fuel_hybrid	title_status_clean	title_status_lien	titl
286424	2015.0	26495.0	0	0	1	0	1	0	
386351	2016.0	57029.0	0	0	1	0	1	0	
482454	2014.0	114488.0	0	0	1	0	1	0	
112489	2011.0	101023.0	0	0	1	0	1	0	
489902	2010.0	70375.0	0	0	1	0	1	0	
450662	2009.0	122598.0	0	0	1	0	1	0	

6 rows × 24 columns

In [37]:
```
X_enc.shape
```

Out[37]:
```
(196884, 24)
```

Perform Training and Testing Split

We will split the data with 33% as test.

In [38]:
```
# split training and testing dataset
X_train, X_test, y_train, y_test = train_test_split(X_enc, y, random_state=66,test_size=0.3
```

Fit First Model

Our first Decision Tree Regressor model will be run on the default parameters that come from [SciKit Learn (https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html)](https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html).

In [39]:
```
# create a regressor object
regressor = DecisionTreeRegressor(random_state = 66)
regressor.fit(X_train, y_train)
```

Out[39]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='deprecated',
                      random_state=66, splitter='best')
```

In [40]:
```
y_predicted = regressor.predict(X_test)
print('Training accuracy: ',regressor.score(X_train,y_train))
print('Test Accuracy: ',regressor.score(X_test,y_test))
```

```
Training accuracy:  0.9878322641478163
Test Accuracy:  0.7326405511046303
```

We see that our training accuracy is 98.8% but our testing accuracy is %73. This means that the model is overfitting the data. In order to mitigate this, I use Sklearn's Randomized Search Cross-Validataion. See the [documentation (https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RandomizedSearchCV.html#sklearn-model-selection-randomizedsearchcv)](https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RandomizedSearchCV.html#sklearn-model-selection-randomizedsearchcv) for more info.

Hyperparameter tuning with RandomizedSearchCV

In [41]:
```
param_grid = {"criterion": ["mse", "mae"],
              "min_samples_split": [10, 20, 40, 50, 60],
              "max_depth": [2, 6, 8, 12, 14],
              "min_samples_leaf": [10 ,20, 40, 100],
              }

n_iter_search = 10

rand_search_cv = RandomizedSearchCV(estimator=regressor,
                                    param_distributions= param_grid,
                                    cv=5,
                                    n_iter=n_iter_search,
                                    n_jobs=-1)
```

Report scores from RandomizedSearchCV (taken from SciKit Learn [Documentation (https://scikit-learn.org/stable/auto_examples/model_selection/plot_randomized_search.html#sphx-glr-auto-examples-model-selection-plot-randomized-search-py)](https://scikit-learn.org/stable/auto_examples/model_selection/plot_randomized_search.html#sphx-glr-auto-examples-model-selection-plot-randomized-search-py))

In [42]:
```
# Utility function to report best scores (taken from Skikit Learn documentations)
def report(results, n_top=3):
    for i in range(1, n_top + 1):
        candidates = np.flatnonzero(results['rank_test_score'] == i)
        for candidate in candidates:
            print("Model with rank: {0}".format(i))
            print("Mean validation score: {0:.3f} (std: {1:.3f})"
                  .format(results['mean_test_score'][candidate],
                          results['std_test_score'][candidate]))
            print("Parameters: {0}".format(results['params'][candidate]))
            print("")
```

In [43]:
```
from time import time
start = time()

rand_search_cv.fit(X_train, y_train)

print("RandomizedSearchCV took %.2f seconds for %d candidates"
      " parameter settings." % ((time() - start), n_iter_search))

report(rand_search_cv.cv_results_)
```

```
RandomizedSearchCV took 2359.94 seconds for 10 candidates parameter settings.
Model with rank: 1
Mean validation score: 0.754 (std: 0.002)
Parameters: {'min_samples_split': 50, 'min_samples_leaf': 20, 'max_depth': 14, 'criterio
n': 'mse'}

Model with rank: 2
Mean validation score: 0.753 (std: 0.001)
Parameters: {'min_samples_split': 20, 'min_samples_leaf': 20, 'max_depth': 12, 'criterio
n': 'mse'}

Model with rank: 3
Mean validation score: 0.751 (std: 0.002)
Parameters: {'min_samples_split': 40, 'min_samples_leaf': 40, 'max_depth': 14, 'criterio
n': 'mse'}
```

In [44]:
```
print("R-Squared::{}".format(rand_search_cv.best_score_))
print("Best Hyperparameters::\n{}".format(rand_search_cv.best_params_))
```

```
R-Squared::0.7542683305409869
Best Hyperparameters::
{'min_samples_split': 50, 'min_samples_leaf': 20, 'max_depth': 14, 'criterion': 'mse'}
```

We can see that the randomized search cross-validatio improved the model accuracy by ~2%.

Further Improvement

Some more work is required to improve the mode accuracy. A few things that could be done:

- Trying reducing the number of levels in the categorical variables.
- Exploring a simpler multi-linear model that only uses numerical data (`price` , `odometer` , and `year`).
- Exploring a more complex model, such as Random Forests to increase the level of accuracy.

In [ ]:
```
```