Predicting sale price of Bulldozers using Machine Learning

1. Problem Definition

> Predict the future sale price of a Bulldozer based on it's characteristics and past sales of similar bulldozers.

2. Data

The data is taken from the Kaggle competition - `Blue Book for Bulldozers` :
https://www.kaggle.com/competitions/bluebook-for-bulldozers/data

There are 3 datasets for the problem -

- Train.csv is the training set, which contains data through the end of 2011.
- Valid.csv is the validation set, which contains data from January 1, 2012 - April 30, 2012.
- Test.csv is the test set which contains data from May 1, 2012 - November 2012.

3. Evaluation

The evaluation metric for this competition is the RMSLE (root mean squared log error) between the actual and predicted auction prices.
Note - In a regression problem, the goal is to reduce the error as much as possible. i.e. for the given problem, reduce RMSLE.

4. Features

Kaggle provides a data dictionary for the features present in the datasets.
Data Dictionary google spreadsheet : https://docs.google.com/spreadsheets/d/1TdR-DKtUNUdwcuawLolL_K8bA28_ms2z_7K5Hza0wng/edit?usp=sharing

Importing Modules

In [60]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn
from sklearn.ensemble import RandomForestRegressor

%matplotlib inline
```

Exploratory Data Analysis (EDA)

In [2]:
```
df = pd.read_csv("data/bluebook-for-bulldozers/TrainAndValid.csv", low_memory = False)
```

In [3]:
```
df.head()
```

Out[3]:

	SalesID	SalePrice	MachineID	ModelID	datasource	auctioneerID	YearMade	MachineHoursCurrentMet
0	1139246	66000.0	999089	3157	121	3.0	2004	68
1	1139248	57000.0	117657	77	121	3.0	1996	4640
2	1139249	10000.0	434808	7009	121	3.0	2001	2838
3	1139251	38500.0	1026470	332	121	3.0	2001	3486
4	1139253	11000.0	1057373	17311	121	3.0	2007	722

5 rows × 53 columns

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 412698 entries, 0 to 412697
Data columns (total 53 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   SalesID                   412698 non-null  int64
 1   SalePrice                 412698 non-null  float64
 2   MachineID                 412698 non-null  int64
 3   ModelID                   412698 non-null  int64
 4   datasource                412698 non-null  int64
 5   auctioneerID              392562 non-null  float64
 6   YearMade                  412698 non-null  int64
 7   MachineHoursCurrentMeter  147504 non-null  float64
 8   UsageBand                 73670 non-null   object
 9   saledate                  412698 non-null  object
 10  fiModelDesc               412698 non-null  object
 11  fiBaseModel               412698 non-null  object
 12  fiSecondaryDesc           271971 non-null  object
 13  fiModelSeries             58667 non-null   object
 14  fiModelDescriptor         74816 non-null   object
 15  ProductSize               196093 non-null  object
 16  fiProductClassDesc        412698 non-null  object
 17  state                     412698 non-null  object
 18  ProductGroup              412698 non-null  object
 19  ProductGroupDesc          412698 non-null  object
 20  Drive_System              107087 non-null  object
 21  Enclosure                 412364 non-null  object
 22  Forks                     197715 non-null  object
 23  Pad_Type                  81096 non-null   object
 24  Ride_Control              152728 non-null  object
 25  Stick                     81096 non-null   object
 26  Transmission              188007 non-null  object
 27  Turbocharged              81096 non-null   object
 28  Blade_Extension           25983 non-null   object
 29  Blade_Width               25983 non-null   object
 30  Enclosure_Type            25983 non-null   object
 31  Engine_Horsepower         25983 non-null   object
 32  Hydraulics                330133 non-null  object
 33  Pushblock                 25983 non-null   object
 34  Ripper                    106945 non-null  object
 35  Scarifier                 25994 non-null   object
 36  Tip_Control               25983 non-null   object
 37  Tire_Size                 97638 non-null   object
 38  Coupler                   220679 non-null  object
```

```
 39  Coupler_System            44974 non-null   object
 40  Grouser_Tracks            44875 non-null   object
 41  Hydraulics_Flow           44875 non-null   object
 42  Track_Type                102193 non-null  object
 43  Undercarriage_Pad_Width   102916 non-null  object
 44  Stick_Length              102261 non-null  object
 45  Thumb                     102332 non-null  object
 46  Pattern_Changer           102261 non-null  object
 47  Grouser_Type              102193 non-null  object
 48  Backhoe_Mounting          80712 non-null   object
 49  Blade_Type                81875 non-null   object
 50  Travel_Controls           81877 non-null   object
 51  Differential_Type         71564 non-null   object
 52  Steering_Controls         71522 non-null   object
dtypes: float64(3), int64(5), object(45)
memory usage: 166.9+ MB
```

In [5]:

```
df.isna().sum()
```

Out[5]:

```
SalesID                          0
SalePrice                        0
MachineID                        0
ModelID                          0
datasource                       0
auctioneerID                 20136
YearMade                         0
MachineHoursCurrentMeter    265194
UsageBand                   339028
saledate                         0
fiModelDesc                      0
fiBaseModel                      0
fiSecondaryDesc             140727
fiModelSeries               354031
fiModelDescriptor           337882
ProductSize                 216605
fiProductClassDesc               0
state                            0
ProductGroup                     0
ProductGroupDesc                 0
Drive_System                305611
Enclosure                      334
Forks                       214983
Pad_Type                    331602
Ride_Control                259970
Stick                       331602
Transmission                224691
Turbocharged                331602
Blade_Extension             386715
Blade_Width                 386715
Enclosure_Type              386715
Engine_Horsepower           386715
Hydraulics                   82565
Pushblock                   386715
Ripper                      305753
Scarifier                   386704
Tip_Control                 386715
Tire_Size                   315060
Coupler                     192019
Coupler_System              367724
Grouser_Tracks              367823
Hydraulics_Flow             367823
Track_Type                  310505
Undercarriage_Pad_Width     309782
Stick_Length                310437
Thumb                       310366
Pattern_Changer             310437
```

```
Grouser_Type                310505
Backhoe_Mounting            331986
Blade_Type                  330823
Travel_Controls             330821
Differential_Type           341134
Steering_Controls           341176
dtype: int64
```

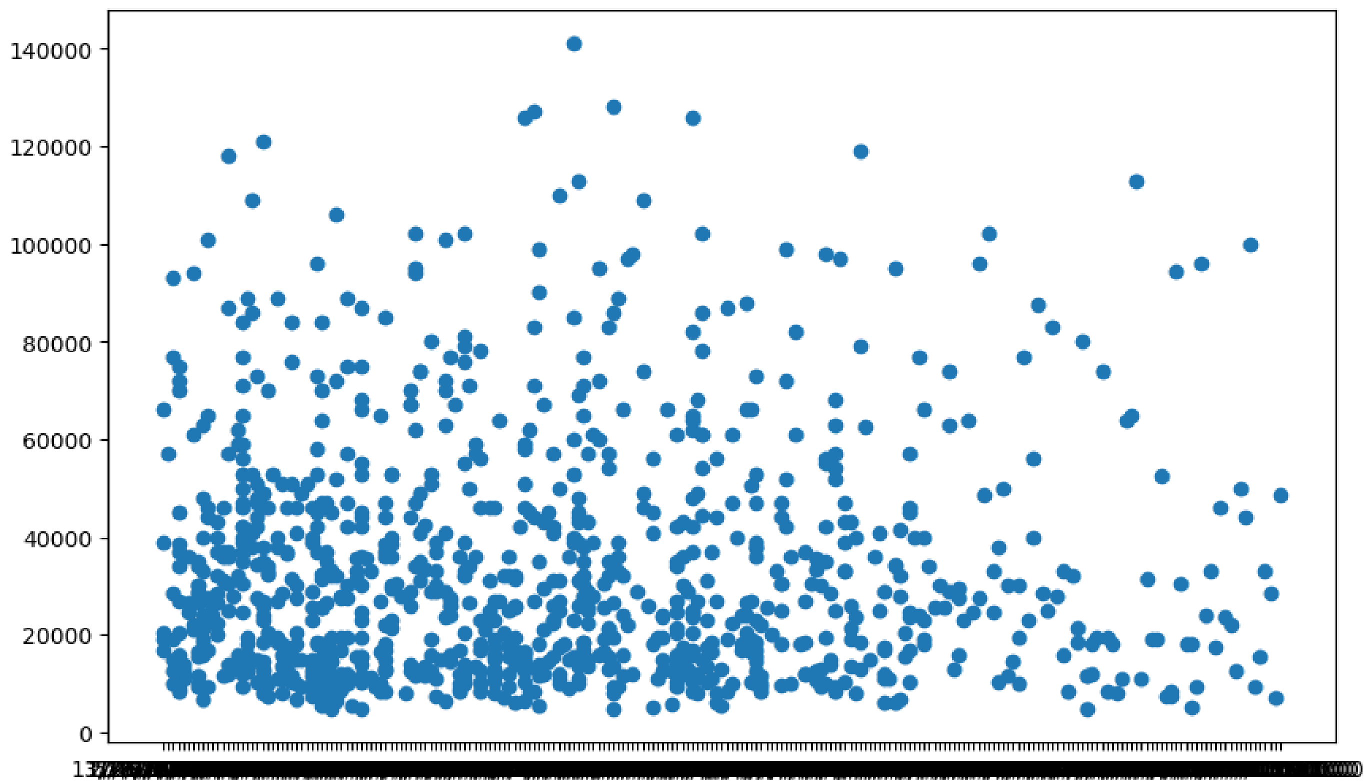
In [6]:
```python
df["saledate"][:10]
```

Out[6]:
```
0    11/16/2006 0:00
1     3/26/2004 0:00
2     2/26/2004 0:00
3     5/19/2011 0:00
4     7/23/2009 0:00
5    12/18/2008 0:00
6     8/26/2004 0:00
7    11/17/2005 0:00
8     8/27/2009 0:00
9      8/9/2007 0:00
Name: saledate, dtype: object
```

In [7]:
```python
df["saledate"].dtype
```

Out[7]:
```
dtype('O')
```

In [8]:
```python
fig, ax = plt.subplots(figsize = (10,6))
ax = plt.scatter(df["saledate"][:1000], df["SalePrice"][:1000]);
```



The saledate column contains datetime data and must be parsed as datetime during importation

In [9]:
```python
# Reimporting with parsed datetime
df = pd.read_csv("data/bluebook-for-bulldozers/TrainAndValid.csv", low_memory=False, par
```

In [10]:
```python
df.head()
```

Out[10]:

	SalesID	SalePrice	MachineID	ModelID	datasource	auctioneerID	YearMade	MachineHoursCurrentMet
0	1139246	66000.0	999089	3157	121	3.0	2004	68

1	1139248	57000.0	117657	77	121	3.0	1996	464C
2	1139249	10000.0	434808	7009	121	3.0	2001	2838
3	1139251	38500.0	1026470	332	121	3.0	2001	3486
4	1139253	11000.0	1057373	17311	121	3.0	2007	722

5 rows × 53 columns

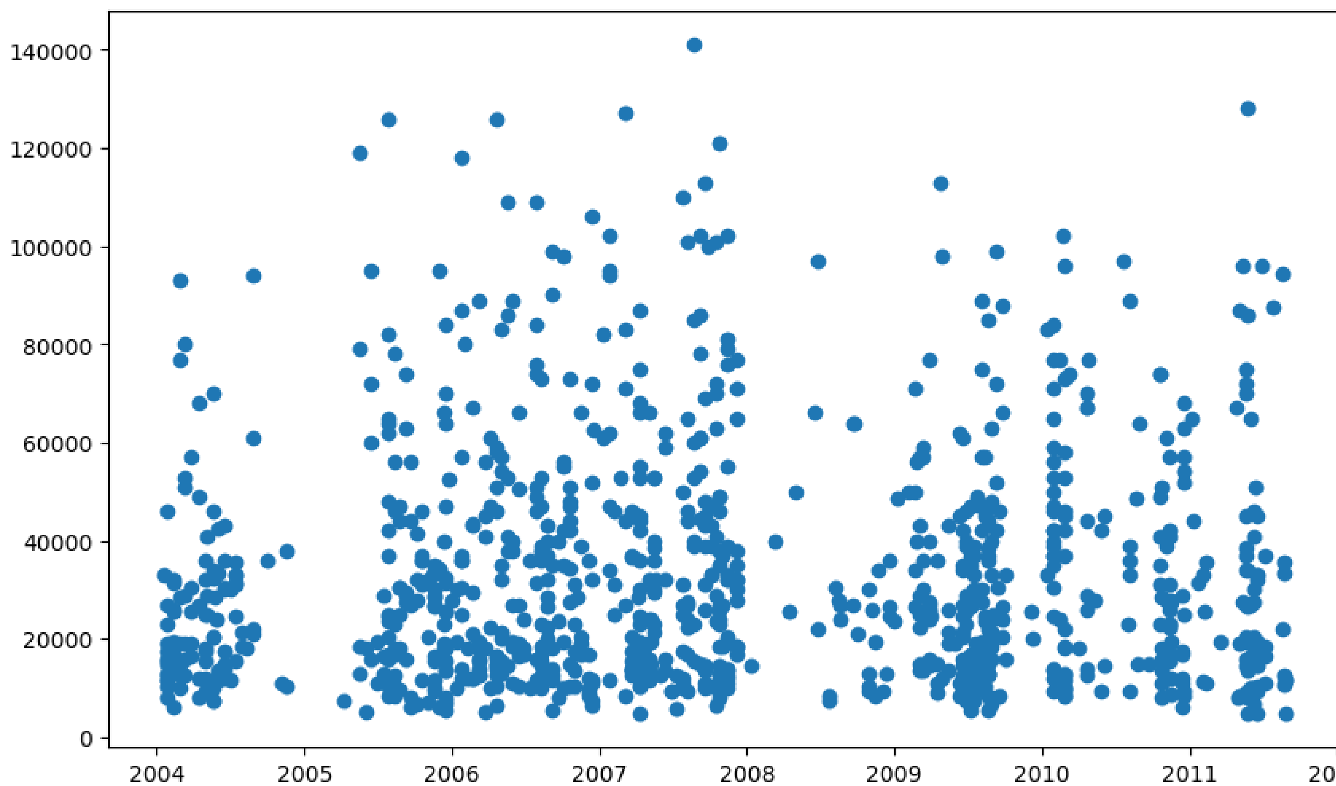
In [11]:
```
df["saledate"][:10]
```

Out[11]:
```
0    2006-11-16
1    2004-03-26
2    2004-02-26
3    2011-05-19
4    2009-07-23
5    2008-12-18
6    2004-08-26
7    2005-11-17
8    2009-08-27
9    2007-08-09
Name: saledate, dtype: datetime64[ns]
```

In [12]:
```
df["saledate"].dtype
```

Out[12]:
```
dtype('<M8[ns]')
```

In [13]:
```
fig, ax = plt.subplots(figsize = (10,6))
ax = plt.scatter(df["saledate"][:1000], df["SalePrice"][:1000])
```



Since Jupyter Notebook truncates the data if the number of features is large let's view all the features in head() using it's transpose.

In [14]:
```
df.head().T
```

Out[14]:

	0	1	2	3	4
SalesID	1139246	1139248	1139249	1139251	1139253
SalePrice	66000.0	57000.0	10000.0	38500.0	11000.0
MachineID	999089	117657	434808	1026470	1057373
ModelID	3157	77	7009	332	17311
datasource	121	121	121	121	121
auctioneerID	3.0	3.0	3.0	3.0	3.0
YearMade	2004	1996	2001	2001	2007
MachineHoursCurrentMeter	68.0	4640.0	2838.0	3486.0	722.0
UsageBand	Low	Low	High	High	Medium
saledate	2006-11-16 00:00:00	2004-03-26 00:00:00	2004-02-26 00:00:00	2011-05-19 00:00:00	2009-07-23 00:00:00
fiModelDesc	521D	950FII	226	PC120-6E	S175
fiBaseModel	521	950	226	PC120	S175
fiSecondaryDesc	D	F	NaN	NaN	NaN
fiModelSeries	NaN	II	NaN	-6E	NaN
fiModelDescriptor	NaN	NaN	NaN	NaN	NaN
ProductSize	NaN	Medium	NaN	Small	NaN
fiProductClassDesc	Wheel Loader - 110.0 to 120.0 Horsepower	Wheel Loader - 150.0 to 175.0 Horsepower	Skid Steer Loader - 1351.0 to 1601.0 Lb Operat...	Hydraulic Excavator, Track - 12.0 to 14.0 Metr...	Skid Steer Loader - 1601.0 to 1751.0 Lb Operat...
state	Alabama	North Carolina	New York	Texas	New York
ProductGroup	WL	WL	SSL	TEX	SSL
ProductGroupDesc	Wheel Loader	Wheel Loader	Skid Steer Loaders	Track Excavators	Skid Steer Loaders
Drive_System	NaN	NaN	NaN	NaN	NaN
Enclosure	EROPS w AC	EROPS w AC	OROPS	EROPS w AC	EROPS
Forks	None or Unspecified	None or Unspecified	None or Unspecified	NaN	None or Unspecified
Pad_Type	NaN	NaN	NaN	NaN	NaN
Ride_Control	None or Unspecified	None or Unspecified	NaN	NaN	NaN
Stick	NaN	NaN	NaN	NaN	NaN
Transmission	NaN	NaN	NaN	NaN	NaN
Turbocharged	NaN	NaN	NaN	NaN	NaN
Blade_Extension	NaN	NaN	NaN	NaN	NaN
Blade_Width	NaN	NaN	NaN	NaN	NaN
Enclosure_Type	NaN	NaN	NaN	NaN	NaN
Engine_Horsepower	NaN	NaN	NaN	NaN	NaN

Hydraulics	2 Valve	2 Valve	Auxiliary	2 Valve	Auxiliary
Pushblock	NaN	NaN	NaN	NaN	NaN
Ripper	NaN	NaN	NaN	NaN	NaN
Scarifier	NaN	NaN	NaN	NaN	NaN
Tip_Control	NaN	NaN	NaN	NaN	NaN
Tire_Size	None or Unspecified	23.5	NaN	NaN	NaN
Coupler	None or Unspecified	None or Unspecified	None or Unspecified	None or Unspecified	None or Unspecified
Coupler_System	NaN	NaN	None or Unspecified	NaN	None or Unspecified
Grouser_Tracks	NaN	NaN	None or Unspecified	NaN	None or Unspecified
Hydraulics_Flow	NaN	NaN	Standard	NaN	Standard
Track_Type	NaN	NaN	NaN	NaN	NaN
Undercarriage_Pad_Width	NaN	NaN	NaN	NaN	NaN
Stick_Length	NaN	NaN	NaN	NaN	NaN
Thumb	NaN	NaN	NaN	NaN	NaN
Pattern_Changer	NaN	NaN	NaN	NaN	NaN
Grouser_Type	NaN	NaN	NaN	NaN	NaN
Backhoe_Mounting	NaN	NaN	NaN	NaN	NaN
Blade_Type	NaN	NaN	NaN	NaN	NaN
Travel_Controls	NaN	NaN	NaN	NaN	NaN
Differential_Type	Standard	Standard	NaN	NaN	NaN
Steering_Controls	Conventional	Conventional	NaN	NaN	NaN

Since we are dealing with a timeseries data, it's better to sort the data according to the saledate

In [15]:
```
df["saledate"].head(10)
```

Out[15]:
```
0    2006-11-16
1    2004-03-26
2    2004-02-26
3    2011-05-19
4    2009-07-23
5    2008-12-18
6    2004-08-26
7    2005-11-17
8    2009-08-27
9    2007-08-09
Name: saledate, dtype: datetime64[ns]
```

Sorting the Dataframe by Saledate

In [16]:
```
df.sort_values(by = ["saledate"], inplace = True)
```

In [17]:
```
df["saledate"].head(10)
```

Out[17]:
```
205615    1989-01-17
```

```
274835   1989-01-31
141296   1989-01-31
212552   1989-01-31
62755    1989-01-31
54653    1989-01-31
81383    1989-01-31
204924   1989-01-31
135376   1989-01-31
113390   1989-01-31
Name: saledate, dtype: datetime64[ns]
```

In [18]:
```
df.head()
```

Out[18]:

	SalesID	SalePrice	MachineID	ModelID	datasource	auctioneerID	YearMade	MachineHoursCurr
205615	1646770	9500.0	1126363	8434	132	18.0	1974	
274835	1821514	14000.0	1194089	10150	132	99.0	1980	
141296	1505138	50000.0	1473654	4139	132	99.0	1978	
212552	1671174	16000.0	1327630	8591	132	99.0	1980	
62755	1329056	22000.0	1336053	4089	132	99.0	1984	

5 rows × 53 columns

Now let's make a copy of the data for further modifications.

Making a copy of the DataFrame

In [19]:
```
df_tmp = df.copy()
```

In [20]:
```
df_tmp.head()
```

Out[20]:

	SalesID	SalePrice	MachineID	ModelID	datasource	auctioneerID	YearMade	MachineHoursCurr
205615	1646770	9500.0	1126363	8434	132	18.0	1974	
274835	1821514	14000.0	1194089	10150	132	99.0	1980	
141296	1505138	50000.0	1473654	4139	132	99.0	1978	
212552	1671174	16000.0	1327630	8591	132	99.0	1980	
62755	1329056	22000.0	1336053	4089	132	99.0	1984	

5 rows × 53 columns

Feature engineering (Enriching data using the saledate feature)

In [21]:
```
df_tmp["saleYear"] = df_tmp["saledate"].dt.year
df_tmp["saleMonth"] = df_tmp["saledate"].dt.month
df_tmp["saleDay"] = df_tmp["saledate"].dt.day
df_tmp["saleDayOfWeek"] = df_tmp["saledate"].dt.dayofweek
```

```
df_tmp["saleDayOfYear"] = df_tmp["saledate"].dt.dayofyear
df_tmp.head().T
```

Out[21]:

	205615	274835	141296	212552	62755
SalesID	1646770	1821514	1505138	1671174	1329056
SalePrice	9500.0	14000.0	50000.0	16000.0	22000.0
MachineID	1126363	1194089	1473654	1327630	1336053
ModelID	8434	10150	4139	8591	4089
datasource	132	132	132	132	132
auctioneerID	18.0	99.0	99.0	99.0	99.0
YearMade	1974	1980	1978	1980	1984
MachineHoursCurrentMeter	NaN	NaN	NaN	NaN	NaN
UsageBand	NaN	NaN	NaN	NaN	NaN
saledate	1989-01-17 00:00:00	1989-01-31 00:00:00	1989-01-31 00:00:00	1989-01-31 00:00:00	1989-01-31 00:00:00
fiModelDesc	TD20	A66	D7G	A62	D3B
fiBaseModel	TD20	A66	D7	A62	D3
fiSecondaryDesc	NaN	NaN	G	NaN	B
fiModelSeries	NaN	NaN	NaN	NaN	NaN
fiModelDescriptor	NaN	NaN	NaN	NaN	NaN
ProductSize	Medium	NaN	Large	NaN	NaN
fiProductClassDesc	Track Type Tractor, Dozer - 105.0 to 130.0 Hor...	Wheel Loader - 120.0 to 135.0 Horsepower	Track Type Tractor, Dozer - 190.0 to 260.0 Hor...	Wheel Loader - Unidentified	Track Type Tractor, Dozer - 20.0 to 75.0 Horse...
state	Texas	Florida	Florida	Florida	Florida
ProductGroup	TTT	WL	TTT	WL	TTT
ProductGroupDesc	Track Type Tractors	Wheel Loader	Track Type Tractors	Wheel Loader	Track Type Tractors
Drive_System	NaN	NaN	NaN	NaN	NaN
Enclosure	OROPS	OROPS	OROPS	EROPS	OROPS
Forks	NaN	None or Unspecified	NaN	None or Unspecified	NaN
Pad_Type	NaN	NaN	NaN	NaN	NaN
Ride_Control	NaN	None or Unspecified	NaN	None or Unspecified	NaN
Stick	NaN	NaN	NaN	NaN	NaN
Transmission	Direct Drive	NaN	Standard	NaN	Standard
Turbocharged	NaN	NaN	NaN	NaN	NaN
Blade_Extension	NaN	NaN	NaN	NaN	NaN
Blade_Width	NaN	NaN	NaN	NaN	NaN
Enclosure_Type	NaN	NaN	NaN	NaN	NaN
Engine_Horsepower	NaN	NaN	NaN	NaN	NaN

Hydraulics	2 Valve	2 Valve	2 Valve	2 Valve	2 Valve
Pushblock	NaN	NaN	NaN	NaN	NaN
Ripper	None or Unspecified	NaN	None or Unspecified	NaN	None or Unspecified
Scarifier	NaN	NaN	NaN	NaN	NaN
Tip_Control	NaN	NaN	NaN	NaN	NaN
Tire_Size	NaN	None or Unspecified	NaN	None or Unspecified	NaN
Coupler	NaN	None or Unspecified	NaN	None or Unspecified	NaN
Coupler_System	NaN	NaN	NaN	NaN	NaN
Grouser_Tracks	NaN	NaN	NaN	NaN	NaN
Hydraulics_Flow	NaN	NaN	NaN	NaN	NaN
Track_Type	NaN	NaN	NaN	NaN	NaN
Undercarriage_Pad_Width	NaN	NaN	NaN	NaN	NaN
Stick_Length	NaN	NaN	NaN	NaN	NaN
Thumb	NaN	NaN	NaN	NaN	NaN
Pattern_Changer	NaN	NaN	NaN	NaN	NaN
Grouser_Type	NaN	NaN	NaN	NaN	NaN
Backhoe_Mounting	None or Unspecified	NaN	None or Unspecified	NaN	None or Unspecified
Blade_Type	Straight	NaN	Straight	NaN	PAT
Travel_Controls	None or Unspecified	NaN	None or Unspecified	NaN	Lever
Differential_Type	NaN	Standard	NaN	Standard	NaN
Steering_Controls	NaN	Conventional	NaN	Conventional	NaN
saleYear	1989	1989	1989	1989	1989
saleMonth	1	1	1	1	1
saleDay	17	31	31	31	31
saleDayOfWeek	1	1	1	1	1
saleDayOfYear	17	31	31	31	31

Now we don't need saledate column so let's drop it. If required, it is present in the original copy of DataFrame `df`.

In [22]:
```
df_tmp.drop("saledate", axis = 1, inplace = True)
df_tmp.head().T
```

Out[22]:

	205615	274835	141296	212552	62755
SalesID	1646770	1821514	1505138	1671174	1329056
SalePrice	9500.0	14000.0	50000.0	16000.0	22000.0
MachineID	1126363	1194089	1473654	1327630	1336053
ModelID	8434	10150	4139	8591	4089

datasource	132	132	132	132	132
auctioneerID	18.0	99.0	99.0	99.0	99.0
YearMade	1974	1980	1978	1980	1984
MachineHoursCurrentMeter	NaN	NaN	NaN	NaN	NaN
UsageBand	NaN	NaN	NaN	NaN	NaN
fiModelDesc	TD20	A66	D7G	A62	D3B
fiBaseModel	TD20	A66	D7	A62	D3
fiSecondaryDesc	NaN	NaN	G	NaN	B
fiModelSeries	NaN	NaN	NaN	NaN	NaN
fiModelDescriptor	NaN	NaN	NaN	NaN	NaN
ProductSize	Medium	NaN	Large	NaN	NaN
fiProductClassDesc	Track Type Tractor, Dozer - 105.0 to 130.0 Hor...	Wheel Loader - 120.0 to 135.0 Horsepower	Track Type Tractor, Dozer - 190.0 to 260.0 Hor...	Wheel Loader - Unidentified	Track Type Tractor, Dozer - 20.0 to 75.0 Horse...
state	Texas	Florida	Florida	Florida	Florida
ProductGroup	TTT	WL	TTT	WL	TTT
ProductGroupDesc	Track Type Tractors	Wheel Loader	Track Type Tractors	Wheel Loader	Track Type Tractors
Drive_System	NaN	NaN	NaN	NaN	NaN
Enclosure	OROPS	OROPS	OROPS	EROPS	OROPS
Forks	NaN	None or Unspecified	NaN	None or Unspecified	NaN
Pad_Type	NaN	NaN	NaN	NaN	NaN
Ride_Control	NaN	None or Unspecified	NaN	None or Unspecified	NaN
Stick	NaN	NaN	NaN	NaN	NaN
Transmission	Direct Drive	NaN	Standard	NaN	Standard
Turbocharged	NaN	NaN	NaN	NaN	NaN
Blade_Extension	NaN	NaN	NaN	NaN	NaN
Blade_Width	NaN	NaN	NaN	NaN	NaN
Enclosure_Type	NaN	NaN	NaN	NaN	NaN
Engine_Horsepower	NaN	NaN	NaN	NaN	NaN
Hydraulics	2 Valve	2 Valve	2 Valve	2 Valve	2 Valve
Pushblock	NaN	NaN	NaN	NaN	NaN
Ripper	None or Unspecified	NaN	None or Unspecified	NaN	None or Unspecified
Scarifier	NaN	NaN	NaN	NaN	NaN
Tip_Control	NaN	NaN	NaN	NaN	NaN
Tire_Size	NaN	None or Unspecified	NaN	None or Unspecified	NaN
Coupler	NaN	None or Unspecified	NaN	None or Unspecified	NaN

Coupler_System	NaN	NaN	NaN	NaN	NaN
Grouser_Tracks	NaN	NaN	NaN	NaN	NaN
Hydraulics_Flow	NaN	NaN	NaN	NaN	NaN
Track_Type	NaN	NaN	NaN	NaN	NaN
Undercarriage_Pad_Width	NaN	NaN	NaN	NaN	NaN
Stick_Length	NaN	NaN	NaN	NaN	NaN
Thumb	NaN	NaN	NaN	NaN	NaN
Pattern_Changer	NaN	NaN	NaN	NaN	NaN
Grouser_Type	NaN	NaN	NaN	NaN	NaN
Backhoe_Mounting	None or Unspecified	NaN	None or Unspecified	NaN	None or Unspecified
Blade_Type	Straight	NaN	Straight	NaN	PAT
Travel_Controls	None or Unspecified	NaN	None or Unspecified	NaN	Lever
Differential_Type	NaN	Standard	NaN	Standard	NaN
Steering_Controls	NaN	Conventional	NaN	Conventional	NaN
saleYear	1989	1989	1989	1989	1989
saleMonth	1	1	1	1	1
saleDay	17	31	31	31	31
saleDayOfWeek	1	1	1	1	1
saleDayOfYear	17	31	31	31	31

Let's explore the sales by US States

In [23]:
```
df_tmp.value_counts("state")
```

Out[23]:
```
state
Florida           67320
Texas             53110
California        29761
Washington        16222
Georgia           14633
Maryland          13322
Mississippi       13240
Ohio              12369
Illinois          11540
Colorado          11529
New Jersey        11156
North Carolina    10636
Tennessee         10298
Alabama           10292
Pennsylvania      10234
South Carolina     9951
Arizona            9364
New York           8639
Connecticut        8276
Minnesota          7885
Missouri           7178
Nevada             6932
Louisiana          6627
Kentucky           5351
```

```
Maine                  5096
Indiana                4124
Arkansas               3933
New Mexico             3631
Utah                   3046
Unspecified            2801
Wisconsin              2745
New Hampshire          2738
Virginia               2353
Idaho                  2025
Oregon                 1911
Michigan               1831
Wyoming                1672
Montana                1336
Iowa                   1336
Oklahoma               1326
Nebraska                866
West Virginia           840
Kansas                  667
Delaware                510
North Dakota            480
Alaska                  430
Massachusetts           347
Vermont                 300
South Dakota            244
Hawaii                  118
Rhode Island             83
Puerto Rico              42
Washington DC             2
dtype: int64
```

In [24]:
```
df_tmp.value_counts("ProductGroupDesc")
```

Out[24]:
```
ProductGroupDesc
Track Excavators        104230
Track Type Tractors      82582
Backhoe Loaders          81401
Wheel Loader             73216
Skid Steer Loaders       45011
Motor Graders            26258
dtype: int64
```

Before we go ahead with modelling we need to convert `string` data into pandas **`categories`**.

Converting string data to pandas categories

In [25]:
```
pd.api.types.is_string_dtype(df["state"])
```

Out[25]:
```
True
```

In [26]:
```
df_tmp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 412698 entries, 205615 to 409203
Data columns (total 57 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   SalesID                   412698 non-null  int64
 1   SalePrice                 412698 non-null  float64
 2   MachineID                 412698 non-null  int64
 3   ModelID                   412698 non-null  int64
 4   datasource                412698 non-null  int64
 5   auctioneerID              392562 non-null  float64
 6   YearMade                  412698 non-null  int64
```

```
 7   MachineHoursCurrentMeter  147504 non-null  float64
 8   UsageBand                 73670 non-null   object 
 9   fiModelDesc               412698 non-null  object 
 10  fiBaseModel               412698 non-null  object 
 11  fiSecondaryDesc           271971 non-null  object 
 12  fiModelSeries             58667 non-null   object 
 13  fiModelDescriptor         74816 non-null   object 
 14  ProductSize               196093 non-null  object 
 15  fiProductClassDesc        412698 non-null  object 
 16  state                     412698 non-null  object 
 17  ProductGroup              412698 non-null  object 
 18  ProductGroupDesc          412698 non-null  object 
 19  Drive_System              107087 non-null  object 
 20  Enclosure                 412364 non-null  object 
 21  Forks                     197715 non-null  object 
 22  Pad_Type                  81096 non-null   object 
 23  Ride_Control              152728 non-null  object 
 24  Stick                     81096 non-null   object 
 25  Transmission              188007 non-null  object 
 26  Turbocharged              81096 non-null   object 
 27  Blade_Extension           25983 non-null   object 
 28  Blade_Width               25983 non-null   object 
 29  Enclosure_Type            25983 non-null   object 
 30  Engine_Horsepower         25983 non-null   object 
 31  Hydraulics                330133 non-null  object 
 32  Pushblock                 25983 non-null   object 
 33  Ripper                    106945 non-null  object 
 34  Scarifier                 25994 non-null   object 
 35  Tip_Control               25983 non-null   object 
 36  Tire_Size                 97638 non-null   object 
 37  Coupler                   220679 non-null  object 
 38  Coupler_System            44974 non-null   object 
 39  Grouser_Tracks            44875 non-null   object 
 40  Hydraulics_Flow           44875 non-null   object 
 41  Track_Type                102193 non-null  object 
 42  Undercarriage_Pad_Width   102916 non-null  object 
 43  Stick_Length              102261 non-null  object 
 44  Thumb                     102332 non-null  object 
 45  Pattern_Changer           102261 non-null  object 
 46  Grouser_Type              102193 non-null  object 
 47  Backhoe_Mounting          80712 non-null   object 
 48  Blade_Type                81875 non-null   object 
 49  Travel_Controls           81877 non-null   object 
 50  Differential_Type         71564 non-null   object 
 51  Steering_Controls         71522 non-null   object 
 52  saleYear                  412698 non-null  int64  
 53  saleMonth                 412698 non-null  int64  
 54  saleDay                   412698 non-null  int64  
 55  saleDayOfWeek             412698 non-null  int64  
 56  saleDayOfYear             412698 non-null  int64  
dtypes: float64(3), int64(10), object(44)
memory usage: 182.6+ MB
```

Let's itereate through the dataframe and check which features have string type values

In [27]:
```python
for col_name , col_content in df_tmp.items():
    if pd.api.types.is_string_dtype(col_content):
        print(col_name)
```

```
UsageBand
fiModelDesc
fiBaseModel
fiSecondaryDesc
fiModelSeries
fiModelDescriptor
```

```
ProductSize
fiProductClassDesc
state
ProductGroup
ProductGroupDesc
Drive_System
Enclosure
Forks
Pad_Type
Ride_Control
Stick
Transmission
Turbocharged
Blade_Extension
Blade_Width
Enclosure_Type
Engine_Horsepower
Hydraulics
Pushblock
Ripper
Scarifier
Tip_Control
Tire_Size
Coupler
Coupler_System
Grouser_Tracks
Hydraulics_Flow
Track_Type
Undercarriage_Pad_Width
Stick_Length
Thumb
Pattern_Changer
Grouser_Type
Backhoe_Mounting
Blade_Type
Travel_Controls
Differential_Type
Steering_Controls
```

Let's change the data type of these features to pandas categories

In [28]:
```python
for col_name, col_content in df_tmp.items():
    if pd.api.types.is_string_dtype(col_content):
        df_tmp[col_name] = col_content.astype("category").cat.as_ordered()
df_tmp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 412698 entries, 205615 to 409203
Data columns (total 57 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   SalesID                   412698 non-null  int64
 1   SalePrice                 412698 non-null  float64
 2   MachineID                 412698 non-null  int64
 3   ModelID                   412698 non-null  int64
 4   datasource                412698 non-null  int64
 5   auctioneerID              392562 non-null  float64
 6   YearMade                  412698 non-null  int64
 7   MachineHoursCurrentMeter  147504 non-null  float64
 8   UsageBand                 73670 non-null   category
 9   fiModelDesc               412698 non-null  category
 10  fiBaseModel               412698 non-null  category
 11  fiSecondaryDesc           271971 non-null  category
 12  fiModelSeries             58667 non-null   category
 13  fiModelDescriptor         74816 non-null   category
```

```
 14  ProductSize               196093 non-null  category
 15  fiProductClassDesc        412698 non-null  category
 16  state                     412698 non-null  category
 17  ProductGroup              412698 non-null  category
 18  ProductGroupDesc          412698 non-null  category
 19  Drive_System              107087 non-null  category
 20  Enclosure                 412364 non-null  category
 21  Forks                     197715 non-null  category
 22  Pad_Type                  81096 non-null   category
 23  Ride_Control              152728 non-null  category
 24  Stick                     81096 non-null   category
 25  Transmission              188007 non-null  category
 26  Turbocharged              81096 non-null   category
 27  Blade_Extension           25983 non-null   category
 28  Blade_Width               25983 non-null   category
 29  Enclosure_Type            25983 non-null   category
 30  Engine_Horsepower         25983 non-null   category
 31  Hydraulics                330133 non-null  category
 32  Pushblock                 25983 non-null   category
 33  Ripper                    106945 non-null  category
 34  Scarifier                 25994 non-null   category
 35  Tip_Control               25983 non-null   category
 36  Tire_Size                 97638 non-null   category
 37  Coupler                   220679 non-null  category
 38  Coupler_System            44974 non-null   category
 39  Grouser_Tracks            44875 non-null   category
 40  Hydraulics_Flow           44875 non-null   category
 41  Track_Type                102193 non-null  category
 42  Undercarriage_Pad_Width   102916 non-null  category
 43  Stick_Length              102261 non-null  category
 44  Thumb                     102332 non-null  category
 45  Pattern_Changer           102261 non-null  category
 46  Grouser_Type              102193 non-null  category
 47  Backhoe_Mounting          80712 non-null   category
 48  Blade_Type                81875 non-null   category
 49  Travel_Controls           81877 non-null   category
 50  Differential_Type         71564 non-null   category
 51  Steering_Controls         71522 non-null   category
 52  saleYear                  412698 non-null  int64
 53  saleMonth                 412698 non-null  int64
 54  saleDay                   412698 non-null  int64
 55  saleDayOfWeek             412698 non-null  int64
 56  saleDayOfYear             412698 non-null  int64
dtypes: category(44), float64(3), int64(10)
memory usage: 63.2 MB
```

We have successfully changed the datatype to category

In [29]:
```python
pd.api.types.is_string_dtype(df_tmp["state"])
```

Out[29]:
```
False
```

In [30]:
```python
pd.api.types.is_categorical_dtype(df_tmp["state"])
```

Out[30]:
```
True
```

In [31]:
```python
df_tmp["state"].cat.categories
```

Out[31]:
```
Index(['Alabama', 'Alaska', 'Arizona', 'Arkansas', 'California', 'Colorado',
       'Connecticut', 'Delaware', 'Florida', 'Georgia', 'Hawaii', 'Idaho',
       'Illinois', 'Indiana', 'Iowa', 'Kansas', 'Kentucky', 'Louisiana',
       'Maine', 'Maryland', 'Massachusetts', 'Michigan', 'Minnesota',
       'Mississippi', 'Missouri', 'Montana', 'Nebraska', 'Nevada',
       'New Hampshire', 'New Jersey', 'New Mexico', 'New York',
```

```
        'North Carolina', 'North Dakota', 'Ohio', 'Oklahoma', 'Oregon',
        'Pennsylvania', 'Puerto Rico', 'Rhode Island', 'South Carolina',
        'South Dakota', 'Tennessee', 'Texas', 'Unspecified', 'Utah', 'Vermont',
        'Virginia', 'Washington', 'Washington DC', 'West Virginia', 'Wisconsin',
        'Wyoming'],
       dtype='object')
```

In [32]:
```
df_tmp["state"].cat.codes[:10]
```

Out[32]:
```
205615    43
274835     8
141296     8
212552     8
62755      8
54653      8
81383      8
204924     8
135376     8
113390     8
dtype: int8
```

In [33]:
```
df_tmp["state"][:10]
```

Out[33]:
```
205615      Texas
274835    Florida
141296    Florida
212552    Florida
62755     Florida
54653     Florida
81383     Florida
204924    Florida
135376    Florida
113390    Florida
Name: state, dtype: category
Categories (53, object): ['Alabama' < 'Alaska' < 'Arizona' < 'Arkansas' ... 'Washington
DC' < 'West Virginia' < 'Wisconsin' < 'Wyoming']
```

We can see that Texas has a code of 43 while Florida has a code of 8.

The code is set alphabetically.

Saving Preprocessed data

In [34]:
```
df_tmp.to_csv("data/bluebook-for-bulldozers/train_valid_tmp.csv", index = False)
```

In [35]:
```
df_tmp = pd.read_csv("data/bluebook-for-bulldozers/train_valid_tmp.csv", low_memory = Fa
```

Dealing with missing data

Our dataset contains a lot of missing data

In [36]:
```
df_tmp.isnull().sum()
```

Out[36]:
```
SalesID                          0
SalePrice                        0
MachineID                        0
ModelID                          0
datasource                       0
auctioneerID                 20136
YearMade                         0
MachineHoursCurrentMeter    265194
UsageBand                   339028
fiModelDesc                      0
```

```
fiBaseModel                     0
fiSecondaryDesc            140727
fiModelSeries              354031
fiModelDescriptor          337882
ProductSize                216605
fiProductClassDesc              0
state                           0
ProductGroup                    0
ProductGroupDesc                0
Drive_System               305611
Enclosure                     334
Forks                      214983
Pad_Type                   331602
Ride_Control               259970
Stick                      331602
Transmission               224691
Turbocharged               331602
Blade_Extension            386715
Blade_Width                386715
Enclosure_Type             386715
Engine_Horsepower          386715
Hydraulics                  82565
Pushblock                  386715
Ripper                     305753
Scarifier                  386704
Tip_Control                386715
Tire_Size                  315060
Coupler                    192019
Coupler_System             367724
Grouser_Tracks             367823
Hydraulics_Flow            367823
Track_Type                 310505
Undercarriage_Pad_Width    309782
Stick_Length               310437
Thumb                      310366
Pattern_Changer            310437
Grouser_Type               310505
Backhoe_Mounting           331986
Blade_Type                 330823
Travel_Controls            330821
Differential_Type          341134
Steering_Controls          341176
saleYear                        0
saleMonth                       0
saleDay                         0
saleDayOfWeek                   0
saleDayOfYear                   0
dtype: int64
```

In [37]:
```
df_tmp.isnull().sum() / len(df_tmp)
```

Out[37]:
```
SalesID                     0.000000
SalePrice                   0.000000
MachineID                   0.000000
ModelID                     0.000000
datasource                  0.000000
auctioneerID                0.048791
YearMade                    0.000000
MachineHoursCurrentMeter    0.642586
UsageBand                   0.821492
fiModelDesc                 0.000000
fiBaseModel                 0.000000
fiSecondaryDesc             0.340993
fiModelSeries               0.857845
fiModelDescriptor           0.818715
ProductSize                 0.524851
```

```
fiProductClassDesc          0.000000
state                       0.000000
ProductGroup                0.000000
ProductGroupDesc            0.000000
Drive_System                0.740520
Enclosure                   0.000809
Forks                       0.520921
Pad_Type                    0.803498
Ride_Control                0.629928
Stick                       0.803498
Transmission                0.544444
Turbocharged                0.803498
Blade_Extension             0.937041
Blade_Width                 0.937041
Enclosure_Type              0.937041
Engine_Horsepower           0.937041
Hydraulics                  0.200062
Pushblock                   0.937041
Ripper                      0.740864
Scarifier                   0.937014
Tip_Control                 0.937041
Tire_Size                   0.763415
Coupler                     0.465277
Coupler_System              0.891024
Grouser_Tracks              0.891264
Hydraulics_Flow             0.891264
Track_Type                  0.752378
Undercarriage_Pad_Width     0.750626
Stick_Length                0.752213
Thumb                       0.752041
Pattern_Changer             0.752213
Grouser_Type                0.752378
Backhoe_Mounting            0.804428
Blade_Type                  0.801610
Travel_Controls             0.801606
Differential_Type           0.826595
Steering_Controls           0.826697
saleYear                    0.000000
saleMonth                   0.000000
saleDay                     0.000000
saleDayOfWeek               0.000000
saleDayOfYear               0.000000
dtype: float64
```

Filling Features with Numerical Data

Let's first see all the features with numerical data

In [38]:

```python
for col_name, col_content in df_tmp.items():
    if pd.api.types.is_numeric_dtype(col_content):
        print(col_name)
```

```
SalesID
SalePrice
MachineID
ModelID
datasource
auctioneerID
YearMade
MachineHoursCurrentMeter
saleYear
saleMonth
saleDay
```

```
saleDayOfWeek
saleDayOfYear
```

Let's check the missing values in numerical features

In [39]:
```python
for col_name, col_content in df_tmp.items():
    if pd.api.types.is_numeric_dtype(col_content):
        if col_content.isnull().sum():
            print(col_name, col_content.isnull().sum())
```

```
auctioneerID 20136
MachineHoursCurrentMeter 265194
```

Let's fill these missing numeric values with median of the feature

In [44]:
```python
for col_name, col_content in df_tmp.items():
    if pd.api.types.is_numeric_dtype(col_content):
        if pd.isnull(col_content).sum():
            df_tmp[col_name] = col_content.fillna(col_content.median())
            df_tmp[col_name + "is_missing"] = pd.isnull(col_content)
            # making new cols to check if data was missing.
```

Let's check for missing values again

In [45]:
```python
for col_name, col_content in df_tmp.items():
    if pd.api.types.is_numeric_dtype(col_content):
        if col_content.isnull().sum():
            print(col_name, col_content.isnull().sum())
```

No missing values left.

Now let's check how many values were filled.

In [46]:
```python
df_tmp["auctioneerIDis_missing"].value_counts()
```

Out[46]:
```
False    392562
True      20136
Name: auctioneerIDis_missing, dtype: int64
```

In [47]:
```python
df_tmp["MachineHoursCurrentMeteris_missing"].value_counts()
```

Out[47]:
```
True     265194
False    147504
Name: MachineHoursCurrentMeteris_missing, dtype: int64
```

Filling missing categories and turning categorical data into numeric data

In [53]:
```python
pd.Categorical(df_tmp["state"]).codes
```

Out[53]:
```
array([43,  8,  8, ...,  4,  4,  4], dtype=int8)
```

By default missing values in pandas has a category of -1

In [55]:
```python
pd.Categorical(df_tmp["UsageBand"]).codes
```

Out[55]:
```
array([-1, -1, -1, ..., -1, -1, -1], dtype=int8)
```

In [56]:
```python
for col_name, col_content in df_tmp.items():
    if not pd.api.types.is_numeric_dtype(col_content):
        # Creating a binary feature showing if the value was missing
        df_tmp[col_name + "_is_missing"] = col_content.isnull()
```

```
        # Turning Categories into Numbers and Filling Null Vals
        df_tmp[col_name] = pd.Categorical(col_content).codes + 1
```

Adding +1 to the category codes will make Null's value from -1 to 0.

In [57]:
```
df_tmp.isnull().sum()
```

Out[57]:
```
SalesID                         0
SalePrice                       0
MachineID                       0
ModelID                         0
datasource                      0
                               ..
Backhoe_Mounting_is_missing     0
Blade_Type_is_missing           0
Travel_Controls_is_missing      0
Differential_Type_is_missing    0
Steering_Controls_is_missing    0
Length: 103, dtype: int64
```

All the null values have been filled

In [58]:
```
df_tmp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 412698 entries, 0 to 412697
Columns: 103 entries, SalesID to Steering_Controls_is_missing
dtypes: bool(46), float64(3), int16(4), int64(10), int8(40)
memory usage: 77.9 MB
```

5. Modelling

Now that we have turned dtypes to Numerical and Filled the missing data, we can start modelling

In [61]:
```
%%time

np.random.seed(0)

X = df_tmp.drop("SalePrice", axis = 1)
y = df_tmp["SalePrice"]

model = RandomForestRegressor(n_jobs = -1, random_state = 0)

model.fit(X, y)
```

```
CPU times: user 11min 31s, sys: 6.46 s, total: 11min 37s
Wall time: 1min 46s
```

Out[61]:
```
▾            RandomForestRegressor
RandomForestRegressor(n_jobs=-1, random_state=0)
```

Let's initally score the model on the same dataset

In [62]:
```
model.score(X, y)
```

Out[62]:
```
0.9875764803061743
```

This scoring metric is on the same set that the model was trained on. So it isn't an accurate representation of the model's generalization

Splitting the data into Training ang Validation Sets

The validation set is the data for the year `2012`

In [67]:
```
df_train = df_tmp[df_tmp["saleYear"] != 2012]
df_val = df_tmp[df_tmp["saleYear"] == 2012]
```

In [68]:
```
len(df_train), len(df_val)
```

Out[68]:
```
(401125, 11573)
```

In [78]:
```
X_train, y_train = df_train.drop("SalePrice", axis = 1), df_train["SalePrice"]
X_val, y_val = df_val.drop("SalePrice", axis = 1), df_val["SalePrice"]
```

In [79]:
```
len(X_train), len(y_train), len(X_val), len(y_val)
```

Out[79]:
```
(401125, 401125, 11573, 11573)
```

Building an evaluation function

In [83]:
```
from sklearn.metrics import mean_squared_log_error, mean_absolute_error, r2_score

def rmsle(y_true, y_preds):
    '''
    Function that returns the Root Mean Squared Log Error (RMSLE) of y_true and y_preds.
    '''
    return np.sqrt(mean_squared_log_error(y_true, y_preds))

def eval_model(model, X_train, X_test, y_train, y_test):
    '''
    Makes prediction and evaluations on given model based on X_train, X_test, y_train an
    '''
    train_preds = model.predict(X_train)
    test_preds = model.predict(X_test)

    eval_scores = {
        "Train Mean Absolute Error" : mean_absolute_error(y_train, train_preds),
        "Test Mean Absolute Error" : mean_absolute_error(y_test, test_preds),
        "Train Root Mean Squared Log Error" : rmsle(y_train, train_preds),
        "Test Root Mean Squared Log Error" : rmsle(y_test, test_preds),
        "Train R^2" : r2_score(y_train, train_preds),
        "Test R^2" : r2_score(y_test, test_preds)
    }
    return eval_scores
```

Testing our model on a subset of the data (to tune the hyperparameters)

In [90]:
```
%%time
model = RandomForestRegressor(n_jobs = -1, random_state = 0, max_samples = 10000)
model.fit(X_train, y_train)
```

```
CPU times: user 22.7 s, sys: 264 ms, total: 22.9 s
Wall time: 3.19 s
```

Out[90]:
```
▾ RandomForestRegressor
RandomForestRegressor(max_samples=10000, n_jobs=-1, random_state=0)
```

In [91]:
```
baseline_scores = eval_model(model, X_train, X_val, y_train, y_val)
baseline_scores
```

Out[91]:
```
{'Train Mean Absolute Error': 5558.52439820505,
 'Test Mean Absolute Error': 7171.1105391860365,
 'Train Root Mean Squared Log Error': 0.25777132630598937,
 'Test Root Mean Squared Log Error': 0.2925990620389206,
 'Train R^2': 0.8606818966052752,
 'Test R^2': 0.832049867497664}
```

Tuning the hyperparameters using RandomizedSearchCV

In [96]:
```
%%time

from sklearn.model_selection import RandomizedSearchCV

rs_grid = {
    "n_estimators": np.arange(10,200,20),
    "max_depth": [None, 3, 5, 10],
    "min_samples_split": np.arange(2,20,2),
    "min_samples_leaf": np.arange(1,20,2),
    "max_features": [0.5, 1, "sqrt"],
    "max_samples": [10000]
}

rs_model = RandomizedSearchCV(RandomForestRegressor(n_jobs = -1, random_state=0),
                              param_distributions = rs_grid,
                              cv = 5,
                              n_iter = 100,
                              verbose = True)
rs_model.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
CPU times: user 5min 18s, sys: 49.6 s, total: 6min 7s
Wall time: 9min 36s
```

Out[96]:
```
▸ RandomizedSearchCV
▸ estimator: RandomForestRegressor
    ▸ RandomForestRegressor
```

In [97]:
```
rs_model.best_params_
```

Out[97]:
```
{'n_estimators': 130,
 'min_samples_split': 10,
 'min_samples_leaf': 3,
 'max_samples': 10000,
 'max_features': 0.5,
 'max_depth': None}
```

In [98]:
```
baseline_scores
```

Out[98]:
```
{'Train Mean Absolute Error': 5558.52439820505,
 'Test Mean Absolute Error': 7171.1105391860365,
 'Train Root Mean Squared Log Error': 0.25777132630598937,
 'Test Root Mean Squared Log Error': 0.2925990620389206,
 'Train R^2': 0.8606818966052752,
 'Test R^2': 0.832049867497664}
```

In [99]:
```
rs_scores = eval_model(rs_model, X_train, X_val, y_train, y_val)
rs_scores
```

Out[99]:
```
{'Train Mean Absolute Error': 5911.904418786114,
 'Test Mean Absolute Error': 7268.799278416505,
 'Train Root Mean Squared Log Error': 0.27010028208693937,
 'Test Root Mean Squared Log Error': 0.29567630218568863,
```

```
 'Train R^2': 0.8437098487721018,
 'Test R^2': 0.8271379483482113}
```

Traininga a model with the tuned hyperparamets

In [102…
```python
tuned_model = RandomForestRegressor(n_estimators = 130,
                                    min_samples_split = 10,
                                    min_samples_leaf = 3,
                                    max_samples = None,
                                    max_features = 0.5,
                                    max_depth = None,
                                    n_jobs = -1,
                                    random_state = 0)
tuned_model.fit(X_train, y_train)
```

Out[102]:
```
RandomForestRegressor
RandomForestRegressor(max_features=0.5, min_samples_leaf=3,
                      min_samples_split=10, n_estimators=130, n_jobs=-1,
                      random_state=0)
```

In [104…
```python
tuned_model_scores = eval_model(tuned_model, X_train, X_val, y_train, y_val)
tuned_model_scores
```

Out[104]:
```
{'Train Mean Absolute Error': 2844.8336474314638,
 'Test Mean Absolute Error': 5884.576654930028,
 'Train Root Mean Squared Log Error': 0.1423311430882674,
 'Test Root Mean Squared Log Error': 0.2417827606636782,
 'Train R^2': 0.9597602190360334,
 'Test R^2': 0.8834509262663633}
```

Making Prediction on the Test Data

In [122…
```python
df_test = pd.read_csv("data/bluebook-for-bulldozers/Test.csv", low_memory=False, parse_d
df_test.head()
```

Out[122]:

	SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	MachineHoursCurrentMeter	Usage
0	1227829	1006309	3168	121	3	1999	3688.0	
1	1227844	1022817	7271	121	3	1000	28555.0	
2	1227847	1031560	22805	121	3	2004	6038.0	M
3	1227848	56204	1269	121	3	2006	8940.0	
4	1227863	1053887	22312	121	3	2005	2286.0	

5 rows × 52 columns

The test data must first be preprocessed to be in the same format as that of our training set

In [123…
```python
X_train.columns
```

Out[123]:
```
Index(['SalesID', 'MachineID', 'ModelID', 'datasource', 'auctioneerID',
       'YearMade', 'MachineHoursCurrentMeter', 'UsageBand', 'fiModelDesc',
       'fiBaseModel',
```

```
        ...
        'Undercarriage_Pad_Width_is_missing', 'Stick_Length_is_missing',
        'Thumb_is_missing', 'Pattern_Changer_is_missing',
        'Grouser_Type_is_missing', 'Backhoe_Mounting_is_missing',
        'Blade_Type_is_missing', 'Travel_Controls_is_missing',
        'Differential_Type_is_missing', 'Steering_Controls_is_missing'],
       dtype='object', length=102)
```

In [124…

```
df_test.columns
```

Out[124]:

```
Index(['SalesID', 'MachineID', 'ModelID', 'datasource', 'auctioneerID',
       'YearMade', 'MachineHoursCurrentMeter', 'UsageBand', 'saledate',
       'fiModelDesc', 'fiBaseModel', 'fiSecondaryDesc', 'fiModelSeries',
       'fiModelDescriptor', 'ProductSize', 'fiProductClassDesc', 'state',
       'ProductGroup', 'ProductGroupDesc', 'Drive_System', 'Enclosure',
       'Forks', 'Pad_Type', 'Ride_Control', 'Stick', 'Transmission',
       'Turbocharged', 'Blade_Extension', 'Blade_Width', 'Enclosure_Type',
       'Engine_Horsepower', 'Hydraulics', 'Pushblock', 'Ripper', 'Scarifier',
       'Tip_Control', 'Tire_Size', 'Coupler', 'Coupler_System',
       'Grouser_Tracks', 'Hydraulics_Flow', 'Track_Type',
       'Undercarriage_Pad_Width', 'Stick_Length', 'Thumb', 'Pattern_Changer',
       'Grouser_Type', 'Backhoe_Mounting', 'Blade_Type', 'Travel_Controls',
       'Differential_Type', 'Steering_Controls'],
      dtype='object')
```

Preprocessing the data

In [125…

```
def preprocess_data(df):

    # Feature Engineering using saledate feature
    df["saleYear"] = df["saledate"].dt.year
    df["saleMonth"] = df["saledate"].dt.month
    df["saleDay"] = df["saledate"].dt.day
    df["saleDayOfWeek"] = df["saledate"].dt.dayofweek
    df["saleDayOfYear"] = df["saledate"].dt.dayofyear
    df.drop("saledate", axis = 1, inplace = True)

    # Converting String data to Categories
    for col_name, col_content in df.items():
        if pd.api.types.is_string_dtype(col_content):
            df[col_name] = col_content.astype("category").cat.as_ordered()

    # Filling data
    for col_name, col_content in df.items():

        # Numerical Data
        if pd.api.types.is_numeric_dtype(col_content):
            if pd.isnull(col_content).sum():
                df[col_name] = col_content.fillna(col_content.median())
                df[col_name + "is_missing"] = pd.isnull(col_content)
                # making new cols to check if data was missing.

        # Categorical Data
        if not pd.api.types.is_numeric_dtype(col_content):
            # Creating a binary feature showing if the value was missing
            df[col_name + "_is_missing"] = col_content.isnull()
            # Turning Categories into Numbers and Filling Null Vals
            df[col_name] = pd.Categorical(col_content).codes + 1

    return df
```

In [126…

```
df_test = preprocess_data(df_test)
df_test.head()
```

Out[126]:

	SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	MachineHoursCurrentMeter	Usage
0	1227829	1006309	3168	121	3	1999	3688.0	
1	1227844	1022817	7271	121	3	1000	28555.0	
2	1227847	1031560	22805	121	3	2004	6038.0	
3	1227848	56204	1269	121	3	2006	8940.0	
4	1227863	1053887	22312	121	3	2005	2286.0	

5 rows × 101 columns

In [127…
```
len(df_test.columns), len(X_train.columns)
```
Out[127]:
```
(101, 102)
```

In [129…
```
set(X_train.columns) - set(df_test.columns)
```
Out[129]:
```
{'auctioneerIDis_missing'}
```

There is no auctioneerID Null values in Test Dataset hence this feature is missing. We can manually add the feature

In [130…
```
df_test["auctioneerIDis_missing"] = False
```

In [139…
```
df_test = df_test.reindex(columns=list(X_train.columns))
```

In [140…
```
len(df_test.columns), len(X_train.columns)
```
Out[140]:
```
(102, 102)
```

Making Predictions on the Test set

In [141…
```
test_preds = tuned_model.predict(df_test)
```

In [142…
```
test_preds
```
Out[142]:
```
array([17347.62069212, 18622.20832936, 49162.08708438, ...,
       12535.01052965, 17110.6827157 , 28608.18839628])
```

In [143…
```
test_preds_df = pd.DataFrame()
test_preds_df["SalesID"] = df_test["SalesID"]
test_preds_df["SalesPrice"] = test_preds
```

In [144…
```
test_preds_df
```
Out[144]:

	SalesID	SalesPrice
0	1227829	17347.620692
1	1227844	18622.208329
2	1227847	49162.087084
3	1227848	68131.719246
4	1227863	54513.445507
...	...	...
12452	6643171	39808.592619

12453	6643173	12412.197032
12454	6643184	12535.010530
12455	6643186	17110.682716
12456	6643196	28608.188396

12457 rows × 2 columns

In [145…
```
test_preds_df.to_csv("data/bluebook-for-bulldozers/predicted_sales_price.csv")
```

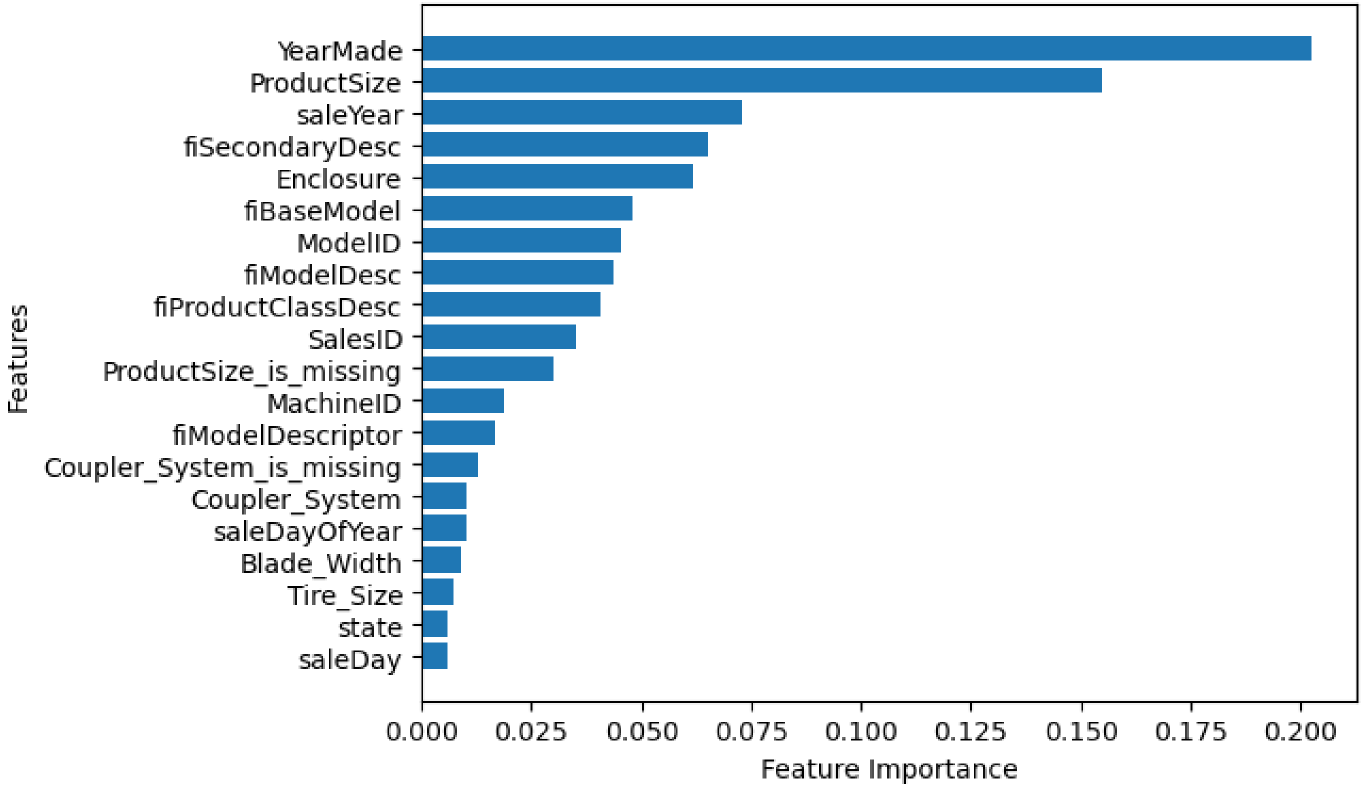
Feature Importance

In [146…
```
tuned_model.feature_importances_
```

Out[146]:
```
array([3.53002628e-02, 1.87088656e-02, 4.52479013e-02, 1.69110698e-03,
       3.31467160e-03, 2.02627988e-01, 3.03853416e-03, 1.06132675e-03,
       4.36857562e-02, 4.82178584e-02, 6.51843745e-02, 4.59642257e-03,
       1.65203621e-02, 1.54674399e-01, 4.05789591e-02, 6.16942667e-03,
       4.80438342e-03, 1.99096712e-03, 3.24624206e-03, 6.15668687e-02,
       5.12113586e-04, 1.57350151e-04, 8.97199123e-04, 1.72662045e-04,
       1.28939126e-03, 1.73156754e-05, 1.57434491e-03, 8.80231196e-03,
       2.74317863e-03, 1.18944838e-03, 4.88483269e-03, 2.81428978e-03,
       3.32742596e-03, 1.04646077e-03, 1.54317753e-03, 7.08262326e-03,
       8.90458833e-04, 1.01528916e-02, 1.97574037e-03, 2.80213202e-03,
       1.11086498e-03, 1.00593958e-03, 2.27993834e-03, 6.42687057e-04,
       6.23172487e-04, 3.74938015e-04, 4.75575766e-04, 2.21729496e-03,
       8.54676772e-04, 2.84932304e-04, 2.18368761e-04, 7.27219199e-02,
       4.25316178e-03, 6.11113228e-03, 3.09441578e-03, 1.01481018e-02,
       1.94622167e-04, 1.39379163e-03, 3.91264434e-04, 0.00000000e+00,
       0.00000000e+00, 2.69055831e-03, 1.32994136e-03, 5.85428315e-03,
       2.98569168e-02, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 6.20083472e-05, 2.01636053e-06, 1.90010416e-04,
       5.17599255e-06, 1.47236631e-04, 4.46252777e-06, 2.46546900e-04,
       2.14456025e-05, 1.28003835e-03, 2.09497500e-03, 1.62409227e-03,
       1.41079037e-03, 1.89688471e-03, 2.68196484e-03, 1.40299783e-03,
       3.40674675e-04, 8.94960103e-04, 3.26197466e-03, 1.62380902e-04,
       1.29479445e-02, 1.84729085e-03, 2.08935085e-03, 4.30793411e-05,
       6.66216316e-05, 6.92148014e-05, 3.88438616e-05, 4.72939387e-05,
       4.84143312e-05, 3.59376961e-04, 1.90987770e-04, 1.01040481e-04,
       8.28277842e-05, 1.06552600e-04])
```

In [147…
```
def plot_features(cols, importance, n = 20):
    df = (pd.DataFrame({"features" : cols,
                      "Feature Importance" : importance}).
          sort_values("Feature Importance", "ascending).
          reset_index(drop = True))
    #plotting
    fig, ax = plt.subplots()
    ax.barh(df["features"][:n], df["Feature Importance"][:n])
    ax.set_ylabel("Features")
    ax.set_xlabel("Feature Importance")
    ax.invert_yaxis();
```

In [151…
```
plot_features(X_train.columns, tuned_model.feature_importances_)
```



YearMade
ProductSize
saleYear
fiSecondaryDesc
Enclosure
fiBaseModel
ModelID
fiModelDesc
fiProductClassDesc
SalesID
ProductSize_is_missing
MachineID
fiModelDescriptor
Coupler_System_is_missing
Coupler_System
saleDayOfYear
Blade_Width
Tire_Size
state
saleDay
Features
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
Feature Importance