

Predicting the Sale Price of Bulldozers using Machine Learning

In this notebook, we're going to go through an example machine learning project with the goal of predicting the sale price of bulldozers.

1. Problem defination

How well we can predict the future sale price of a bulldozer, given its characteristics and previous examples of how much similar bulldozer have been sold for?

2. Data

The data is downloaded from the kaggle Bluebook for Bulldozer competition:

<https://www.kaggle.com/competitions/bluebook-for-bulldozers/data>

There are 3 main datasets:

- 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 You make predictions on this set throughout the majority of the competition. Your score on this set is used to create the public leaderboard.
- Test.csv is the test set, which won't be released until the last week of the competition. It contains data from May 1, 2012 - November 2012. Your score on the test set determines your final rank for the competition.

3. Evaluation

The evaluation metric for this competition is the RMSLE (root mean squared log error) between the actual and predicted auction prices.

For more on the evaluation of this project check: <https://www.kaggle.com/competitions/bluebook-for-bulldozers/overview/evaluation>

Note: The goal for most regression evaluation metrics is to minimize the error. For example, our goal for this project will be to build a machine learning model which minimize RMSLE (root mean squared log error).

4. Features

Kaggle provides a data dictionary detailing all of the features of the data. View this data here: D:\F Drive\Complete Machine Learning and Data Science Zero to Mastery\12. Milestone Project 2 Supervised Learning (Time Series Data)\bluebook-for-bulldozers

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import sklearn
```

In [2]:

```
# import training and validation sets
df = pd.read_csv("data/bluebook-for-bulldozers/TrainAndValid.csv",
                 low_memory=False)
```

In [3]:

```
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 [4]:
```

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

```
Out[4]:
```

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

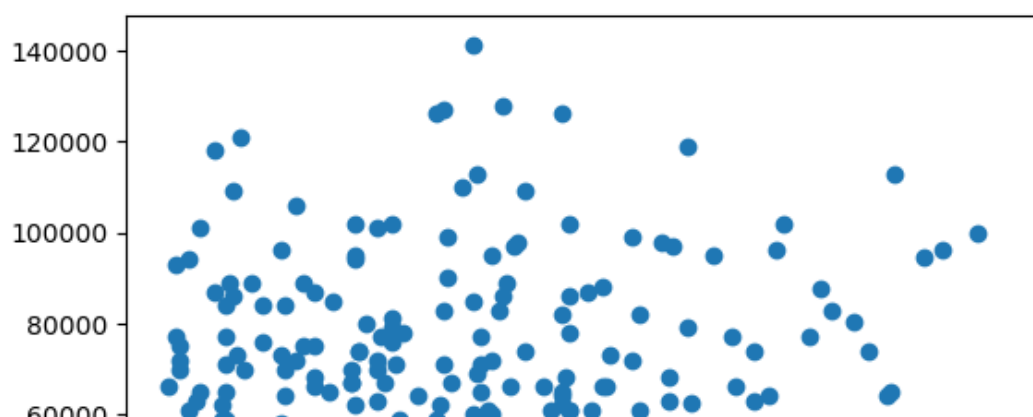
dtype: int64

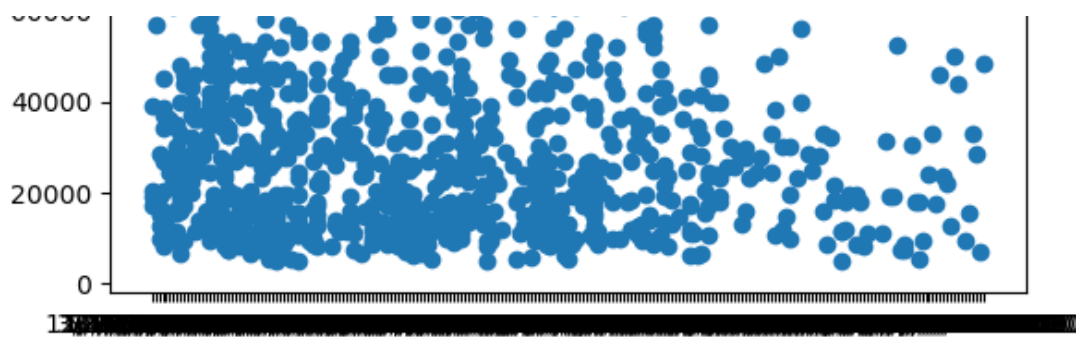
In [5]:

```
fig, ax = plt.subplots()
ax.scatter(df["saledate"][:1000], df["SalePrice"][:1000])
```

Out[5]:

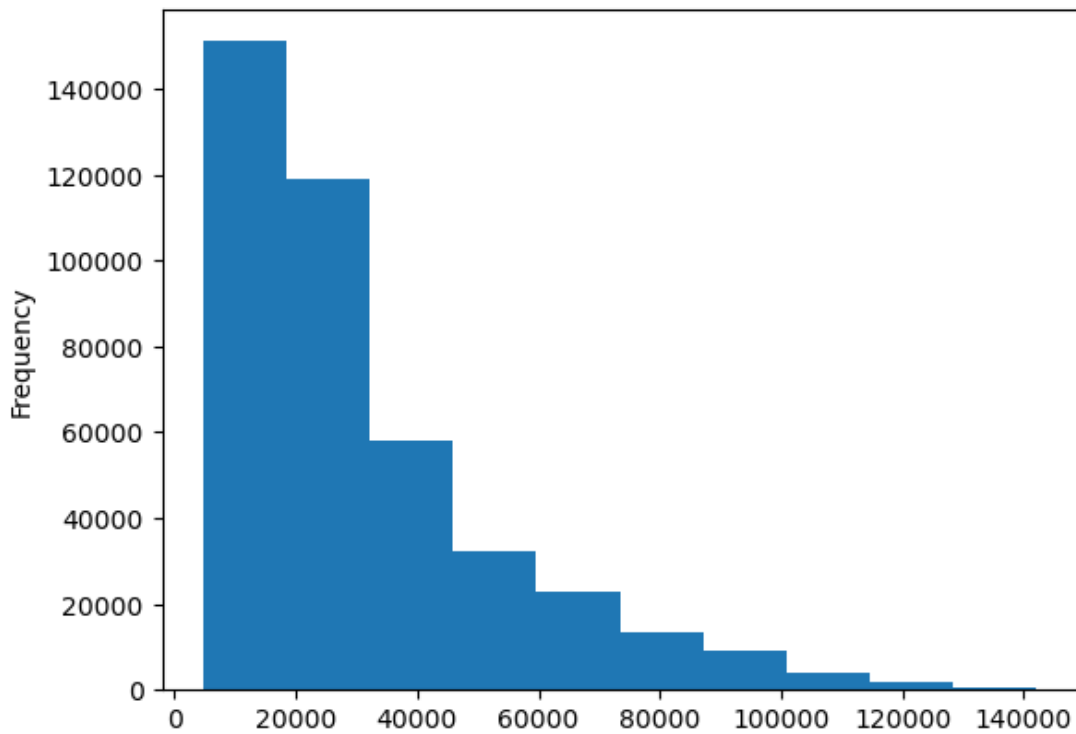
<matplotlib.collections.PathCollection at 0x15587646f70>





In [6]:

```
df.SalePrice.plot.hist();
```



Parsing date

When we work with time series data, we want to enrich the time & date component as much as possible.

We can do that by telling pandas which of our columns has dates in it using the `parse_dates` parameter.

In [7]:

```
# Import data again but this time parse dates
df = pd.read_csv("data/bluebook-for-bulldozers/TrainAndValid.csv",
                 low_memory=False,
                 parse_dates=["saledate"])
```

In [8]:

```
df.saledate.dtype
```

Out[8]:

```
dtype('<M8[ns]')
```

In [9]:

```
df.saledate[:1000]
```

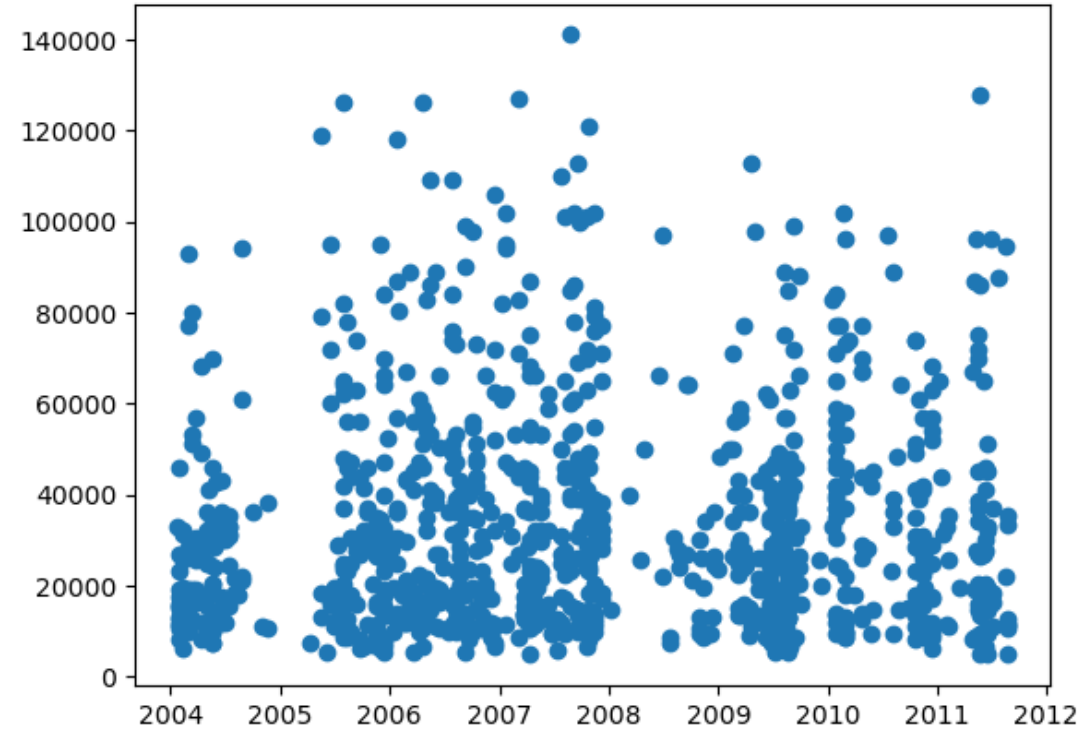
Out[9]:

```
0    2006-11-16
1    2004-03-26
2    2004-03-26
```

```
2      2004-02-20
3      2011-05-19
4      2009-07-23
...
995    2009-07-16
996    2007-06-14
997    2005-09-22
998    2005-07-28
999    2011-06-16
Name: saledate, Length: 1000, dtype: datetime64[ns]
```

In [10]:

```
fig, ax = plt.subplots()
ax.scatter(df["saledate"][:1000], df["SalePrice"][:1000]);
```



In [11]:

```
df.head()
```

Out[11]:

	SalesID	SalePrice	MachineID	ModelID	datasource	auctioneerID	YearMade	MachineHoursCurrentMeter	UsageBand	sa
0	1139246	66000.0	999089	3157	121	3.0	2004	68.0	Low	
1	1139248	57000.0	117657	77	121	3.0	1996	4640.0	Low	
2	1139249	10000.0	434808	7009	121	3.0	2001	2838.0	High	
3	1139251	38500.0	1026470	332	121	3.0	2001	3486.0	High	
4	1139253	11000.0	1057373	17311	121	3.0	2007	722.0	Medium	

5 rows x 53 columns



In [12]:

```
df.head().T
```

Out[12]:

	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	NaN	None or

	NaN 0	NaN 1	Unspecified 2	NaN 3	Unspecified 4
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

In [13]:

```
df.saledate.head(20)
```

Out[13]:

```
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
10   2008-08-21
11   2006-08-24
12   2005-10-20
13   2006-01-26
14   2006-01-03
15   2006-11-16
16   2007-06-14
17   2010-01-28
18   2006-03-09
19   2005-11-17
Name: saledate, dtype: datetime64[ns]
```

Sort DataFrame by saledate

When working with time series data, it's a good idea to sort it by date.

In [14]:

```
# Sort DataFrame in date order
df.sort_values(by=["saledate"], inplace=True, ascending=True)
df.saledate.head(20)
```

Out[14]:

```
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
201021    1989-01-31
```

```
204924 1989-01-31
135376 1989-01-31
113390 1989-01-31
113394 1989-01-31
116419 1989-01-31
32138 1989-01-31
127610 1989-01-31
76171 1989-01-31
127000 1989-01-31
128130 1989-01-31
127626 1989-01-31
55455 1989-01-31
55454 1989-01-31
Name: saledate, dtype: datetime64[ns]
```

Make a copy of original DataFrame

I make a copy of the original DataFrame so when I manipulate the copy, I'll still got the original data.

In [15]:

```
# Make a copy
df_tmp = df.copy()
```

In [16]:

```
df_tmp.saledate.head(20)
```

Out[16]:

```
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
113394 1989-01-31
116419 1989-01-31
32138 1989-01-31
127610 1989-01-31
76171 1989-01-31
127000 1989-01-31
128130 1989-01-31
127626 1989-01-31
55455 1989-01-31
55454 1989-01-31
Name: saledate, dtype: datetime64[ns]
```

Add datetime parameters for saledate column

In [17]:

```
df_tmp[:1].saledate.dt.year
```

Out[17]:

```
205615 1989
Name: saledate, dtype: int64
```

In [18]:

```
df_tmp[:1].saledate.dt.day
```

Out[18]:

```
205615 17
Name: saledate, dtype: int64
```


In [19]:

```
df_tmp[:1].saledate
```

Out[19]:

205615 1989-01-17
Name: saledate, dtype: datetime64[ns]

In [20]:

```
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
```

In [21]:

```
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	203615	274835	141236	212532	62143
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

In [22]:

```
# Now I've enriched our DataFrame with the date time features, now I can remove 'saledate'
df_tmp.drop("saledate", axis=1, inplace=True)
```

In [23]:

```
# Check the values of different columns
df_tmp.state.value_counts()
```

Out[23]:

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
Name: state, dtype: int64
```

5. Modelling

I've done enough EDA (exploratory data analysis). I will start to do some model-driven EDA.

In [24]:

```
# Let's build a machine learning model
from sklearn.ensemble import RandomForestRegressor

model = RandomForestRegressor(n_jobs=-1,
                             random_state=42)

model.fit(df_tmp.drop("SalePrice", axis=1), df_tmp["SalePrice"])
```

ValueError

Traceback (most recent call last)

Input In [24], in <cell line: 7>()

```

2 from sklearn.ensemble import RandomForestRegressor
4 model = RandomForestRegressor(n_jobs=-1,
5                               random_state=42)
----> 7 model.fit(df_tmp.drop("SalePrice", axis=1), df_tmp["SalePrice"])

```

```

File ~\anaconda3\lib\site-packages\sklearn\ensemble\_forest.py:331, in BaseForest.fit(self, X, y, sample_weight)
    329 if issparse(y):
    330     raise ValueError("sparse multilabel-indicator for y is not supported.")
--> 331 X, y = self._validate_data(
    332     X, y, multi_output=True, accept_sparse="csc", dtype=DTYPE
    333 )
    334 if sample_weight is not None:
    335     sample_weight = _check_sample_weight(sample_weight, X)

```

```

File ~\anaconda3\lib\site-packages\sklearn\base.py:596, in BaseEstimator._validate_data(self, X, y, reset, validate_separately, **check_params)
    594 y = check_array(y, input_name="y", **check_y_params)
    595 else:
--> 596 X, y = check_X_y(X, y, **check_params)
    597 out = X, y
    599 if not no_val_X and check_params.get("ensure_2d", True):

```

```

File ~\anaconda3\lib\site-packages\sklearn\utils\validation.py:1074, in check_X_y(X, y, accept_sparse, accept_large_sparse, dtype, order, copy, force_all_finite, ensure_2d, allow_nd, multi_output, ensure_min_samples, ensure_min_features, y_numeric, estimator)
    1069 estimator_name = _check_estimator_name(estimator)
    1070 raise ValueError(
    1071     f"{estimator_name} requires y to be passed, but the target y is None"
    1072 )
-> 1074 X = check_array(
    1075     X,
    1076     accept_sparse=accept_sparse,
    1077     accept_large_sparse=accept_large_sparse,
    1078     dtype=dtype,
    1079     order=order,
    1080     copy=copy,
    1081     force_all_finite=force_all_finite,
    1082     ensure_2d=ensure_2d,
    1083     allow_nd=allow_nd,
    1084     ensure_min_samples=ensure_min_samples,
    1085     ensure_min_features=ensure_min_features,
    1086     estimator=estimator,
    1087     input_name="X",
    1088 )
    1090 y = _check_y(y, multi_output=multi_output, y_numeric=y_numeric, estimator=estimator)
    1092 check_consistent_length(X, y)

```

```

File ~\anaconda3\lib\site-packages\sklearn\utils\validation.py:856, in check_array(array, accept_sparse, accept_large_sparse, dtype, order, copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples, ensure_min_features, estimator, input_name)
    854 array = array.astype(dtype, casting="unsafe", copy=False)
    855 else:
--> 856 array = np.asarray(array, order=order, dtype=dtype)
    857 except ComplexWarning as complex_warning:
    858     raise ValueError(
    859         "Complex data not supported\n{}\n".format(array)
    860     ) from complex_warning

```

```

File ~\anaconda3\lib\site-packages\pandas\core\generic.py:2064, in NDFrame.__array__(self, dtype)
    2063 def __array__(self, dtype: npt.DTypeLike | None = None) -> np.ndarray:
-> 2064     return np.asarray(self._values, dtype=dtype)

```

ValueError: could not convert string to float: 'Low'

In [25]:

```
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

In [26]:

```
df_tmp["UsageBand"].dtype
```

Out[26]:

dtype('O')

In [27]:

```
df_tmp.isna().sum()
```

Out[27]:

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

Converting string to categories

One way I can turn all our data into numbers is by converting them into pandas categories.

I can check different datatypes compatible with pandas here: https://pandas.pydata.org/pandas-docs/version/1.4/reference/general_utility_functions.html

In [28]:

```
pd.api.types.is_string_dtype(df_tmp["UsageBand"])
```

Out[28]:

True

In [29]:

```
# Find the columns which contains string
```

```
for label, content in df_tmp.items(): # here label means columns and content refers column names
    if pd.api.types.is_string_dtype(content):
        print(label)
```

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

In [30]:

```
# Creating a dictionary
```

```
random_dict = {"key1": "hello",
               "key2": "world"}
```

```
for key, value in random_dict.items():
    print(f"this is a key: {key}",
          f"this has a value: {value}")
```

```
this is a key: key1 this has a value: hello
this is a key: key2 this has a value: world
```

In [31]:

```
# This will turn all of the string values into category values

for label, content in df_tmp.items():
    if pd.api.types.is_string_dtype(content):
        df_tmp[label] = content.astype("category").cat.as_ordered() # as_ordered() function is for arrange data alphabetically
```

In [32]:

```
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
```



```
50 differential_type      71504 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
```

In [33]:

```
df_tmp.state.cat.categories
```

Out[33]:

```
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 [34]:

```
df_tmp.state.cat.codes # Though the states showing as string/object but behind the scene
state names datatype changed to int.
```

Out[34]:

```
205615      43
274835       8
141296       8
212552       8
62755        8
..
410879       4
412476       4
411927       4
407124       4
409203       4
Length: 412698, dtype: int8
```

In [35]:

```
df_tmp.state.value_counts()
```

Out[35]:

```
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
```

```
Connecticut      8270
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
Name: state, dtype: int64
```

Still we've a bunch of missing data...

In [36]:

```
# Check the missing data
df_tmp.isnull().sum()/len(df_tmp) * 100
```

Out[36]:

```
SalesID          0.000000
SalePrice        0.000000
MachineID        0.000000
ModelID          0.000000
datasource       0.000000
auctioneerID     4.879113
YearMade         0.000000
MachineHoursCurrentMeter 64.258610
UsageBand        82.149174
fiModelDesc      0.000000
fiBaseModel      0.000000
fiSecondaryDesc  34.099269
fiModelSeries    85.784520
fiModelDescriptor 81.871490
ProductSize      52.485110
fiProductClassDesc 0.000000
state            0.000000
ProductGroup     0.000000
ProductGroupDesc 0.000000
Drive_System     74.051970
Enclosure        0.080931
Forks            52.092087
Pad_Type         80.349796
Ride_Control     62.992794
Stick            80.349796
Transmission     54.444412
```

Turbocharged 80.349796
Blade_Extension 93.704113
Blade_Width 93.704113
Enclosure_Type 93.704113
Engine_Horsepower 93.704113
Hydraulics 20.006155
Pushblock 93.704113
Ripper 74.086378
Scarifier 93.701448
Tip_Control 93.704113
Tire_Size 76.341538
Coupler 46.527727
Coupler_System 89.102443
Grouser_Tracks 89.126431
Hydraulics_Flow 89.126431
Track_Type 75.237825
Undercarriage_Pad_Width 75.062637
Stick_Length 75.221348
Thumb 75.204144
Pattern_Changer 75.221348
Grouser_Type 75.237825
Backhoe_Mounting 80.442842
Blade_Type 80.161038
Travel_Controls 80.160553
Differential_Type 82.659475
Steering_Controls 82.669652
saleYear 0.000000
saleMonth 0.000000
saleDay 0.000000
saleDayOfWeek 0.000000
saleDayOfYear 0.000000
dtype: float64

Save preprocessed data

In [37]:

```
# Export current tmp dataframe
df_tmp.to_csv("data/bluebook-for-bulldozers/train_tmp.csv",
              index=False)
```

In [38]:

```
# Import preprocessed data
df_tmp = pd.read_csv("data/bluebook-for-bulldozers/train_tmp.csv",
                    low_memory=False)
df_tmp.head().T
```

Out[38]:

	0	1	2	3	4
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 ⁰	NaN ¹	NaN ²	NaN ³	NaN ⁴
fiModelDescriptor	NaN	NaN	NaN	NaN	NaN
ProductSize	Medium	NaN	Large	NaN	NaN
fiProductClassDesc	Track Type Tractor, Dozer - 105.0 to 130.0 Horsepower	Wheel Loader - 120.0 to 135.0 Horsepower	Track Type Tractor, Dozer - 190.0 to 260.0 Horsepower	Wheel Loader - Unidentified	Track Type Tractor, Dozer - 20.0 to 75.0 Horsepower
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

Steering_Controls	nan	Conventional	nan	Conventional	nan
	0	1	2	3	4
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

In [39]:

```
df_tmp.isna().sum()
```

Out[39]:

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

```
saleDayOfYear  
dtype: int64
```

Fill missing values

1. Fill numerical missing values

In [40]:

```
# Finding which columns are numeric  
for label, content in df_tmp.items():  
    if pd.api.types.is_numeric_dtype(content):  
        print(label)
```

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

In [41]:

```
# Checking numeric or non-numeric  
df_tmp.ModelID
```

Out[41]:

```
0          8434  
1         10150  
2          4139  
3          8591  
4          4089  
...  
412693      5266  
412694     19330  
412695     17244  
412696      3357  
412697      4701  
Name: ModelID, Length: 412698, dtype: int64
```

In [42]:

```
# Check for which numeric columns have null values  
for label, content in df_tmp.items():  
    if pd.api.types.is_numeric_dtype(content):  
        if pd.isnull(content).sum():  
            print(label)
```

```
auctioneerID  
MachineHoursCurrentMeter
```

In [43]:

```
# Fill empty/null numeric rows with the median  
for label, content in df_tmp.items():  
    if pd.api.types.is_numeric_dtype(content):  
        if pd.isnull(content).sum():  
            # Add a binary column which tells us if the data was missing or not  
            df_tmp[label+"_is_missing"] = pd.isnull(content)  
            # Fill missing numeric values with median (We are using median rather than m  
            ean, because If data contains outliers such as the 1000 in our example, then you would ty  
            pically rather use the median because otherwise the value of the mean would be dominated
```

```
by the outliers rather than the typical values)
df_tmp[label] = content.fillna(content.median())
```

In [45]:

```
# Check if there's any null numeric values
for label, content in df_tmp.items():
    if pd.api.types.is_numeric_dtype(content):
        if pd.isnull(content).sum():
            print(label)
```

In [46]:

```
# Check to see how many examples were missing
df_tmp.auctioneerID_is_missing.value_counts()
```

Out[46]:

```
False    392562
True      20136
Name: auctioneerID_is_missing, dtype: int64
```

In [47]:

```
df_tmp.isna().sum()
```

Out[47]:

SalesID	0
SalePrice	0
MachineID	0
ModelID	0
datasource	0
auctioneerID	0
YearMade	0
MachineHoursCurrentMeter	0
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	210266

```
Thumb 310388
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
auctioneerID_is_missing 0
MachineHoursCurrentMeter_is_missing 0
dtype: int64
```

Filling and turning categorical variables into numbers

In [48]:

```
# Check for columns which aren't numeric
for label, content in df_tmp.items():
    if not pd.api.types.is_numeric_dtype(content):
        print(label)
```

```
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
```


In [49]:

```
# Turn categorical variables into numbers and fill missing
for label, content in df_tmp.items():
    if not pd.api.types.is_numeric_dtype(content):
        # Add binary column to indicate whether samples had missing values
        df_tmp[label+"_is_missing"] = pd.isnull(content)
        # Turn categories into numbers and add +1
        df_tmp[label] = pd.Categorical(content).codes+1
```

In [50]:

```
pd.Categorical(df_tmp["state"]).codes+1
```

Out[50]:

```
array([44,  9,  9, ...,  5,  5,  5], dtype=int8)
```

In [51]:

```
pd.Categorical(df_tmp["UsageBand"]).codes # NOTE: for missing values -1 is showing. So,
to fill those missing values we need to add +1
```

Out[51]:

```
array([0, 0, 0, ..., 0, 0, 0], dtype=int8)
```

In [52]:

```
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
```

In [53]:

```
df_tmp.head().T
```

Out[53]:

	0	1	2	3	4
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
...
Backhoe_Mounting_is_missing	False	True	False	True	False
Blade_Type_is_missing	False	True	False	True	False
Travel_Controls_is_missing	False	True	False	True	False
Differential_Type_is_missing	True	False	True	False	True
Steering_Controls_is_missing	True	False	True	False	True

103 rows x 5 columns

In [54]:

```
df_tmp.isna().sum()
```

Out[54]:

```
SalesID      0
SalePrice    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

```

Now that all of data is numeric as well as my dataframe has no missing values, I should be able to build a machine learning model.

In [55]:

```
len(df_tmp)
```

Out[55]:

412698

In [56]:

```

%%time
#Instantiated model
model = RandomForestRegressor(n_jobs=-1,
                             random_state=42)

# Fit the model
model.fit(df_tmp.drop("SalePrice", axis=1), df_tmp["SalePrice"])

```

CPU times: total: 28min 40s

Wall time: 1min 54s

Out[56]:

```

▼      RandomForestRegressor
RandomForestRegressor(n_jobs=-1, random_state=42)

```

In [57]:

```

# Score the model
model.score(df_tmp.drop("SalePrice", axis=1), df_tmp["SalePrice"])

```

Out[57]:

0.9875468079970562

Splitting data into train/validation sets

In [58]:

```
df_tmp.saleYear
```

Out[58]:

```

0      1989
1      1989
2      1989
3      1989
4      1989
...
412693  2012
412694  2012
412695  2012
412696  2012
412697  2012
Name: saleYear, Length: 412698, dtype: int64

```

In [59]:

```
df_tmp.saleYear.value_counts()
```

Out[59]:

```
2009    43849
2008    39767
2011    35197
2010    33390
2007    32208
2006    21685
2005    20463
2004    19879
2001    17594
2000    17415
2002    17246
2003    15254
1998    13046
1999    12793
2012    11573
1997     9785
1996     8829
1995     8530
1994     7929
1993     6303
1992     5519
1991     5109
1989     4806
1990     4529
Name: saleYear, dtype: int64
```

In [60]:

```
# Splitting data into training and validation
df_val = df_tmp[df_tmp.saleYear == 2012]
df_train = df_tmp[df_tmp.saleYear != 2012]

len(df_train), len(df_val)
```

Out[60]:

```
(401125, 11573)
```

In [61]:

```
# Split data into X and y
X_train, y_train = df_train.drop("SalePrice", axis=1), df_train.SalePrice
X_valid, y_valid = df_val.drop("SalePrice", axis=1), df_val.SalePrice
X_train.shape, y_train.shape, X_valid.shape, y_valid.shape
```

Out[61]:

```
((401125, 102), (401125,), (11573, 102), (11573,))
```

In [62]:

```
y_train
```

Out[62]:

```
0          9500.0
1         14000.0
2         50000.0
3         16000.0
4         22000.0
...
401120      29000.0
401121      11000.0
401122      11000.0
401123      18000.0
401124      13500.0
Name: SalePrice. Length: 401125. dtype: float64
```

Building an evaluation function

In [64]:

```
# Create evaluation function (the competition uses RMSLE)
from sklearn.metrics import mean_squared_log_error, mean_absolute_error, r2_score

def rmsle(y_test, y_preds):
    """
    Calculate root mean squared log error between predictions and ture labels.
    """
    return np.sqrt(mean_squared_log_error(y_test, y_preds))

# Create a function to evaluate model on a few different values
def show_scores(model):
    train_preds = model.predict(X_train)
    val_preds = model.predict(X_valid)
    scores = {"Training MAE": mean_absolute_error(y_train, train_preds),
              "Valid MAE": mean_absolute_error(y_valid, val_preds),
              "Training RMSLE": rmsle(y_train, train_preds),
              "Valid RMSLE": rmsle(y_valid, val_preds),
              "Training R^2": r2_score(y_train, train_preds),
              "Valid R^2": r2_score(y_valid, val_preds)}
    return scores
```

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

In [65]:

```
# # This takes far too long (time)... for experimenting

# %%time
# model = RandomForestRegressor(n_jobs=-1,
#                               random_state=42)

# model.fit(X_train, y_train)
```

In [66]:

```
len(X_train)
```

Out[66]:

401125

In [67]:

```
# Change max_samples value
model = RandomForestRegressor(n_jobs=-1,
                              random_state=42,
                              max_samples=10000)
```

In [68]:

```
%%time
# Cutting down the max number of samples each estimator can see imporves training time.
model.fit(X_train, y_train)
```

CPU times: total: 50.2 s

Wall time: 3.6 s

Out[68]:

```
▼ RandomForestRegressor
RandomForestRegressor(max_samples=10000, n_jobs=-1, random_state=42)
```

In [69]:

```
(X_train.shape[0] * 100) / 1000000
```

Out[69]:

40.1125

In [70]:

```
10000 * 100
```

Out[70]:

1000000

In [71]:

```
show_scores(model)
```

Out[71]:

```
{'Training MAE': 5561.2988092240585,
 'Valid MAE': 7177.26365505919,
 'Training RMSLE': 0.257745378256977,
 'Valid RMSLE': 0.29362638671089003,
 'Training R^2': 0.8606658995199189,
 'Valid R^2': 0.8320374995090507}
```

Hyperparameter tuning with RandomizedSearchCV

In [72]:

```
%%time
from sklearn.model_selection import RandomizedSearchCV

# Different RandomForestRegressor hyperparameters
rf_grid = {"n_estimators": np.arange(10, 100, 10),
           "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", "auto"],
           "max_samples": [10000]}

# Instantiate RandomizedSearchCV model
rs_model = RandomizedSearchCV(RandomForestRegressor(n_jobs=-1,
                                                    random_state=42),
                              param_distributions=rf_grid,
                              n_iter=100,
                              cv=5,
                              verbose=True)

# Fit the RandomizedSearchCV model
rs_model.fit(X_train, y_train)
```

Fitting 5 folds for each of 100 candidates, totalling 500 fits

C:\Users\Hero Clament\anaconda3\lib\site-packages\sklearn\ensemble_forest.py:416: Future Warning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.

warn(

C:\Users\Hero Clament\anaconda3\lib\site-packages\sklearn\ensemble_forest.py:416: Future Warning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.

warn(

C:\Users\Hero Clament\anaconda3\lib\site-packages\sklearn\ensemble_forest.py:416: Future Warning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.

warn(

C:\Users\Hero Clament\anaconda3\lib\site-packages\sklearn\ensemble_forest.py:416: Future Warning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To

warning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for `RandomForestRegressors` and `ExtraTreesRegressors`.

is also the default value for `RandomForestRegressor` and `ExtraTreesRegressor`.

[illegible]

[illegible]

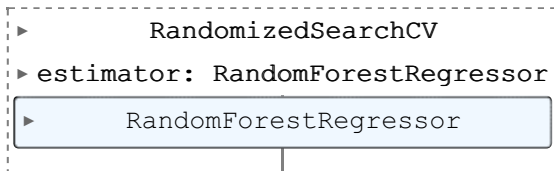
warning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for `RandomForestRegressors` and `ExtraTreesRegressors`.

is also the default value for `RandomForestRegressor` and `ExtraTreesRegressor`.

```
C:\Users\Hero Clament\anaconda3\lib\site-packages\sklearn\ensemble\_forest.py:416: Future
Warning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To
keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it
is also the default value for RandomForestRegressors and ExtraTreesRegressors.
warn(
C:\Users\Hero Clament\anaconda3\lib\site-packages\sklearn\ensemble\_forest.py:416: Future
Warning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To
keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it
is also the default value for RandomForestRegressors and ExtraTreesRegressors.
warn(
```

CPU times: total: 6min 52s
Wall time: 11min 10s

Out[72]:



In [73]:

```
# Find the best model hyperparameters
rs_model.best_params_
```

Out[73]:

```
{'n_estimators': 70,
 'min_samples_split': 18,
 'min_samples_leaf': 1,
 'max_samples': 10000,
 'max_features': 'auto',
 'max_depth': None}
```

In [74]:

```
# Evaluate the RandomizedSearch model
show_scores(rs_model)
```

Out[74]:

```
{'Training MAE': 5868.130564628453,
 'Valid MAE': 7402.897892083917,
 'Training RMSLE': 0.26820268248315415,
 'Valid RMSLE': 0.299808571068006,
 'Training R^2': 0.8447963614628694,
 'Valid R^2': 0.8190401132153241}
```

Training a model with best hyperparameter

Note: These were found after 100 iterations of `RandomizedSearchCV`

In [75]:

```
%%time

# Most ideal hyperparameters
ideal_model = RandomForestRegressor(n_estimators=70,
                                   min_samples_split=2,
                                   min_samples_leaf=3,
                                   max_features=0.5,
                                   n_jobs=-1,
                                   max_samples=None,
                                   max_depth=None,
                                   random_state=42) # Random state so our results are r
e producible

# Fit the ideal model
ideal_model.fit(X_train, y_train)
```

CPU times: total: 9min 25s
Wall time: 38.9 s

Out[75]:

```
RandomForestRegressor  
RandomForestRegressor(max_features=0.5, min_samples_leaf=3, n_estimators=70,  
                        n_jobs=-1, random_state=42)
```

In [76]:

```
# Scores for ideal model (trained on all data)  
show_scores(ideal_model)
```

Out[76]:

```
{'Training MAE': 2517.532396966851,  
 'Valid MAE': 5919.7841407788055,  
 'Training RMSLE': 0.12836315365062645,  
 'Valid RMSLE': 0.24361757440413018,  
 'Training R^2': 0.9677638308179852,  
 'Valid R^2': 0.8818719316864689}
```

In [77]:

```
# Scores for rs_model (only on 10000 data)  
show_scores(rs_model)
```

Out[77]:

```
{'Training MAE': 5868.130564628453,  
 'Valid MAE': 7402.897892083917,  
 'Training RMSLE': 0.26820268248315415,  
 'Valid RMSLE': 0.299808571068006,  
 'Training R^2': 0.8447963614628694,  
 'Valid R^2': 0.8190401132153241}
```

Make predictions on test data

In [78]:

```
# Import the test data  
df_test = pd.read_csv("data/bluebook-for-bulldozers/Test.csv",  
                      low_memory=False,  
                      parse_dates=["saledate"])  
df_test.head()
```

Out[78]:

	SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	MachineHours	CurrentMeter	UsageBand	saledate	fiM
0	1227829	1006309	3168	121	3	1999		3688.0	Low	2012-05-03	
1	1227844	1022817	7271	121	3	1000		28555.0	High	2012-05-10	
2	1227847	1031560	22805	121	3	2004		6038.0	Medium	2012-05-10	E
3	1227848	56204	1269	121	3	2006		8940.0	High	2012-05-10	
4	1227863	1053887	22312	121	3	2005		2286.0	Low	2012-05-10	

5 rows x 52 columns



In [79]:


```
# Make predictions on test dataset
test_preds = ideal_model.predict(df_test)
```

C:\Users\Hero Clament\anaconda3\lib\site-packages\sklearn\base.py:493: FutureWarning: The feature names should match those that were passed during fit. Starting version 1.2, an error will be raised.

Feature names unseen at fit time:

- saledate

Feature names seen at fit time, yet now missing:

- Backhoe_Mounting_is_missing
- Blade_Extension_is_missing
- Blade_Type_is_missing
- Blade_Width_is_missing
- Coupler_System_is_missing
- ...

```
warnings.warn(message, FutureWarning)
```

ValueError Traceback (most recent call last)

Input In [79], in <cell line: 2>()

```
1 # Make predictions on test dataset
----> 2 test_preds = ideal_model.predict(df_test)
```

File ~\anaconda3\lib\site-packages\sklearn\ensemble_forest.py:991, in ForestRegressor.predict(self, X)

```
989 check_is_fitted(self)
990 # Check data
--> 991 X = self._validate_X_predict(X)
993 # Assign chunk of trees to jobs
994 n_jobs, _, _ = _partition_estimators(self.n_estimators, self.n_jobs)
```

File ~\anaconda3\lib\site-packages\sklearn\ensemble_forest.py:605, in BaseForest._validate_X_predict(self, X)

```
602 """
603 Validate X whenever one tries to predict, apply, predict_proba."""
604 check_is_fitted(self)
--> 605 X = self._validate_data(X, dtype=DTYPE, accept_sparse="csr", reset=False)
606 if issparse(X) and (X.indices.dtype != np.intc or X.indptr.dtype != np.intc):
607     raise ValueError("No support for np.int64 index based sparse matrices")
```

File ~\anaconda3\lib\site-packages\sklearn\base.py:577, in BaseEstimator._validate_data(self, X, y, reset, validate_separately, **check_params)

```
575     raise ValueError("Validation should be done on X, y or both.")
576 elif not no_val_X and no_val_y:
--> 577     X = check_array(X, input_name="X", **check_params)
578     out = X
579 elif no_val_X and not no_val_y:
```

File ~\anaconda3\lib\site-packages\sklearn\utils\validation.py:856, in check_array(array, accept_sparse, accept_large_sparse, dtype, order, copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples, ensure_min_features, estimator, input_name)

```
854     array = array.astype(dtype, casting="unsafe", copy=False)
855     else:
--> 856     array = np.asarray(array, order=order, dtype=dtype)
857 except ComplexWarning as complex_warning:
858     raise ValueError(
859         "Complex data not supported\n{}\n".format(array)
860     ) from complex_warning
```

File ~\anaconda3\lib\site-packages\pandas\core\generic.py:2064, in NDFrame.__array__(self, dtype)

```
2063 def __array__(self, dtype: npt.DTypeLike | None = None) -> np.ndarray:
-> 2064     return np.asarray(self._values, dtype=dtype)
```

ValueError: could not convert string to float: 'Low'

Preprocessing the test dataset (getting the test dataset in the same format as our training dataset)

In [80]:

```
def preprocess_data(df):  
    """  
    Performes transformations on df and returns transformed df.  
    """  
    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)  
  
    # Fill the numeric rows with median  
    for label, content in df.items():  
        if pd.api.types.is_numeric_dtype(content):  
            if pd.isnull(content).sum():  
                # Add a binary column which tells us if the data was missing or not  
                df[label+"_is_missing"] = pd.isnull(content)  
                # Fill missing numeric values with median (We are using median rather than  
                # an mean, because If data contains outliers such as the 1000 in our example, then you would  
                # typically rather use the median because otherwise the value of the mean would be dominated  
                # by the outliers rather than the typical values)  
                df[label] = content.fillna(content.median())  
            # Fill categorical missing data and turn categories into numbers  
        for label, content in df.items():  
            if not pd.api.types.is_numeric_dtype(content):  
                # Add binary column to indicate whether samples had missing values  
                df[label+"_is_missing"] = pd.isnull(content)  
                # We add +1 to the category code because pandas encodes missing categories as  
                -1  
                df[label] = pd.Categorical(content).codes+1  
  
    return df
```

In [81]:

```
# Process the test data  
df_test = preprocess_data(df_test)  
df_test.head()
```

Out[81]:

	SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	MachineHoursCurrentMeter	UsageBand	fiModelDesc
0	1227829	1006309	3168	121	3	1999	3688.0	2	499
1	1227844	1022817	7271	121	3	1000	28555.0	1	831
2	1227847	1031560	22805	121	3	2004	6038.0	3	1177
3	1227848	56204	1269	121	3	2006	8940.0	1	287
4	1227863	1053887	22312	121	3	2005	2286.0	2	566

5 rows x 101 columns



In [82]:

```
# Make predictions on updated test data  
test_preds = ideal_model.predict(df_test)
```

C:\Users\Hero Clament\anaconda3\lib\site-packages\sklearn\base.py:493: FutureWarning: The feature names should match those that were passed during fit. Starting version 1.2, an error will be raised.

Feature names seen at fit time, yet now missing:

- auctioneerID_is_missing

warnings.warn(message, FutureWarning)

ValueError

Traceback (most recent call last)


```

ValueError: ...
Input In [82], in <cell line: 2>()
      1 # Make predictions on updated test data
----> 2 test_preds = ideal_model.predict(df_test)

File ~\anaconda3\lib\site-packages\sklearn\ensemble\_forest.py:991, in ForestRegressor.pr
edict(self, X)
      989 check_is_fitted(self)
      990 # Check data
--> 991 X = self._validate_X_predict(X)
      993 # Assign chunk of trees to jobs
      994 n_jobs, _, _ = _partition_estimators(self.n_estimators, self.n_jobs)

File ~\anaconda3\lib\site-packages\sklearn\ensemble\_forest.py:605, in BaseForest._valida
te_X_predict(self, X)
      602 """
      603 Validate X whenever one tries to predict, apply, predict_proba."""
      604 check_is_fitted(self)
--> 605 X = self._validate_data(X, dtype=DTYPE, accept_sparse="csr", reset=False)
      606 if issparse(X) and (X.indices.dtype != np.intc or X.indptr.dtype != np.intc):
      607     raise ValueError("No support for np.int64 index based sparse matrices")

File ~\anaconda3\lib\site-packages\sklearn\base.py:600, in BaseEstimator._validate_data(s
elf, X, y, reset, validate_separately, **check_params)
      597 out = X, y
      599 if not no_val_X and check_params.get("ensure_2d", True):
--> 600     self._check_n_features(X, reset=reset)
      602 return out

File ~\anaconda3\lib\site-packages\sklearn\base.py:400, in BaseEstimator._check_n_feature
s(self, X, reset)
      397 return
      399 if n_features != self.n_features_in_:
--> 400     raise ValueError(
      401         f"X has {n_features} features, but {self.__class__.__name__} "
      402         f"is expecting {self.n_features_in_} features as input."
      403     )

```

ValueError: X has 101 features, but RandomForestRegressor is expecting 102 features as input.

In [83]:

```
X_train.head()
```

Out[83]:

	SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	MachineHoursCurrentMeter	UsageBand	fiModelDesc
0	1646770	1126363	8434	132	18.0	1974	0.0	0	4593
1	1821514	1194089	10150	132	99.0	1980	0.0	0	1820
2	1505138	1473654	4139	132	99.0	1978	0.0	0	2348
3	1671174	1327630	8591	132	99.0	1980	0.0	0	1819
4	1329056	1336053	4089	132	99.0	1984	0.0	0	2119

5 rows x 102 columns

In [84]:

```
# We can find how the columns differ using sets
set(X_train.columns) - set(df_test.columns)
```

Out[84]:

```
{'auctioneerID_is_missing'}
```

In [85]:

```
# Manually adjust df test to have auctioneerID is missing column
```

```
df_test["auctioneerID_is_missing"] = False
df_test.head()
```

Out[85]:

	SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	MachineHoursCurrentMeter	UsageBand	fiModelDesc
0	1227829	1006309	3168	121	3	1999	3688.0	2	499
1	1227844	1022817	7271	121	3	1000	28555.0	1	831
2	1227847	1031560	22805	121	3	2004	6038.0	3	1177
3	1227848	56204	1269	121	3	2006	8940.0	1	287
4	1227863	1053887	22312	121	3	2005	2286.0	2	566

5 rows x 102 columns

Finally test dataframe has the same features as the training dataframe and now I can make predictions!

In [86]:

```
# Make predictions on the test data
test_preds = ideal_model.predict(df_test)
```

C:\Users\Hero Clament\anaconda3\lib\site-packages\sklearn\base.py:493: FutureWarning: The feature names should match those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names must be in the same order as they were in fit.

```
warnings.warn(message, FutureWarning)
```

In [87]:

```
test_preds
```

Out[87]:

```
array([19817.21371882, 20122.20068027, 51645.47488226, ...,
       13902.27581942, 20413.00896722, 30952.35752343])
```

In [88]:

```
len(test_preds)
```

Out[88]:

12457

I've made some predictions but they are not in the same format Kaggle is asking for:

<https://www.kaggle.com/competitions/bluebook-for-bulldozers/overview/evaluation>

In [89]:

```
# Format predictions into the same format Kaggle is after
df_preds = pd.DataFrame()
df_preds["SalesID"] = df_test["SalesID"]
df_preds["SalesPrice"] = test_preds
df_preds
```

Out[89]:

	SalesID	SalesPrice
0	1227829	19817.213719
1	1227844	20122.200680
2	1227847	51645.474882
3	1227848	61693.202948

4	SalePrice	SalePrice
...
12452	6643171	47432.284580
12453	6643173	15891.095522
12454	6643184	13902.275819
12455	6643186	20413.008967
12456	6643196	30952.357523

12457 rows × 2 columns

In [90]:

```
# Export prediction data to csv
df_preds.to_csv("data/bluebook-for-bulldozers/test_predictions.csv", index=False)
```

Feature importance

Feature impotance seeks to fugure out which different attributes or features of the dataset were most important when need to predict the target value (SalePrice)

In [91]:

```
# Find feature importance of our ideal model
ideal_model.feature_importances_, len(ideal_model.feature_importances_)
```

Out[91]:

```
(array([3.60960567e-02, 2.02177121e-02, 3.86157178e-02, 1.94105532e-03,
        3.78908183e-03, 2.04181240e-01, 3.26628759e-03, 1.11768940e-03,
        4.59202806e-02, 4.10168720e-02, 6.54292748e-02, 4.01984150e-03,
        1.52024105e-02, 1.50716489e-01, 4.72622672e-02, 7.12267097e-03,
        2.67254321e-03, 1.98210252e-03, 3.62633952e-03, 6.02980419e-02,
        4.92716722e-04, 6.37713685e-05, 1.17656302e-03, 2.86932591e-04,
        9.49393707e-04, 3.01793841e-05, 1.73117640e-03, 7.40277708e-03,
        6.89207470e-04, 1.29833277e-03, 3.83225459e-03, 2.87894201e-03,
        3.82986895e-03, 1.79518107e-03, 4.95762192e-04, 6.27456507e-03,
        8.88684450e-04, 1.41856592e-02, 4.01781038e-04, 3.86466881e-03,
        1.12954041e-03, 9.88219772e-04, 2.15663678e-03, 6.92267712e-04,
        4.87480250e-04, 3.75179793e-04, 2.74313846e-04, 1.74030601e-03,
        1.14402467e-03, 1.75339734e-04, 4.97037057e-04, 7.28930089e-02,
        4.92682705e-03, 7.27169970e-03, 3.68050204e-03, 1.12618568e-02,
        1.96856176e-04, 1.64530102e-03, 4.32044558e-04, 0.00000000e+00,
        0.00000000e+00, 3.00276175e-03, 1.52018155e-03, 6.87192417e-03,
        3.09070677e-02, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
        0.00000000e+00, 6.35293804e-04, 1.53418365e-06, 1.11549648e-04,
        7.43348598e-06, 1.65009692e-04, 2.68785369e-06, 3.62241039e-04,
        1.37263502e-05, 2.68817995e-03, 2.26370317e-03, 5.63107573e-03,
        1.93814933e-04, 1.76818016e-03, 4.19436426e-05, 7.65459051e-04,
        2.20660259e-03, 1.30943132e-03, 2.61594775e-03, 1.51268708e-04,
        1.35002335e-02, 1.32066854e-03, 1.36272524e-03, 5.02479576e-05,
        1.18068999e-04, 4.51654367e-05, 1.23834936e-04, 9.40691761e-05,
        3.50127461e-05, 3.41651301e-04, 1.67564278e-04, 1.61629835e-04,
        3.14984997e-04, 9.62904946e-05]),
102)
```

Above array is representing 102 columns of our dataset.

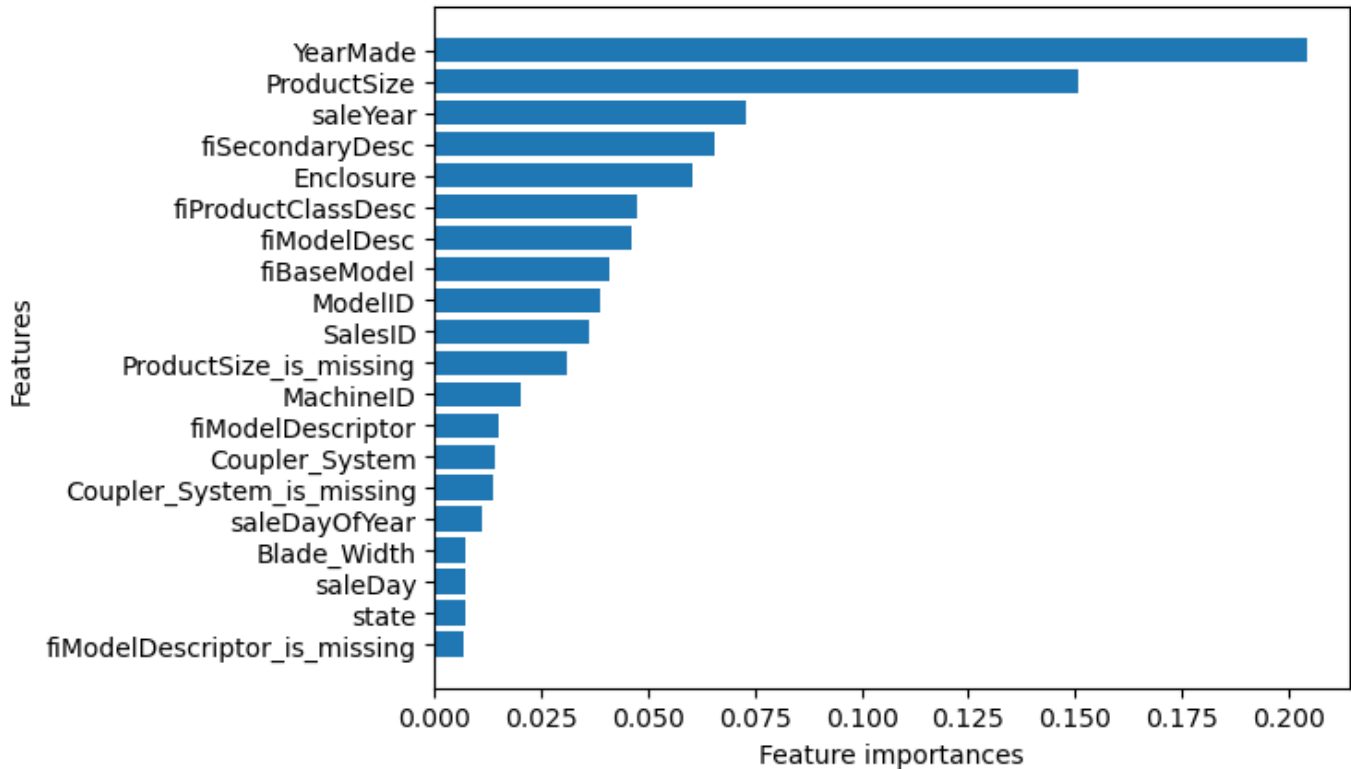
In [92]:

```
# Helper function for plotting feature importance
def plot_features(columns, importances, n=20):
    df = (pd.DataFrame({"features": columns,
                        "feature_importances": importances})
          .sort_values("feature_importances", ascending=False)
          .reset_index(drop=True))
```

```
# Plot the DataFrame
fig, ax = plt.subplots()
ax.barh(df["features"][:n], df["feature_importances"][:20])
ax.set_ylabel("Features")
ax.set_xlabel("Feature importances")
ax.invert_yaxis()
```

In [93]:

```
plot_features(X_train.columns, ideal_model.feature_importances_)
```



In [94]:

```
df["ProductSize"].value_counts()
```

Out[94]:

```
Medium          64342
Large / Medium  51297
Small           27057
Mini            25721
Large           21396
Compact          6280
Name: ProductSize, dtype: int64
```

In [95]:

```
df["Enclosure"].value_counts()
```

Out[95]:

```
OROPS          177971
EROPS          141769
EROPS w AC      92601
EROPS AC         18
NO ROPS           3
None or Unspecified  2
Name: Enclosure, dtype: int64
```