# Predicting the Sale Price of Bulldozers using Machine Learning

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        %matplotlib inline
        import seaborn as sns
In [6]: pd , np ,plt , sns
Out[6]: (<module 'pandas' from 'D:\\Projects\\bulldozer price prediction\\env\\Lib
        \\site-packages\\pandas\\ init .py'>,
         <module 'numpy' from 'D:\\Projects\\bulldozer price prediction\\env\\Lib</pre>
        \\site-packages\\numpy\\ init .py'>,
         <module 'matplotlib.pyplot' from 'D:\\Projects\\bulldozer price prediction</pre>
        \\env\\Lib\\site-packages\\matplotlib\\pyplot.py'>,
         <module 'seaborn' from 'D:\\Projects\\bulldozer price prediction\\env\\Lib
        \\site-packages\\seaborn\\ init .py'>)
In [7]: df = pd.read_csv("data/TrainAndValid.csv" , low_memory = False)
In [8]: 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	•	107087 non-null	
21	Drive_System Enclosure	412364 non-null	object 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
25 26	Transmission	188007 non-null	object
27		81096 non-null	-
28	Turbocharged	25983 non-null	object
29	Blade_Extension Blade Width	25983 non-null	object
30	Enclosure Type	25983 non-null	object
31	<b>—</b> * *		object
32	Engine_Horsepower	25983 non-null 330133 non-null	object
	Hydraulics Pushblock		object
33	Ripper	25983 non-null	object
34	• •	106945 non-null 25994 non-null	object
35	Scarifier Tin Control		object
36 27	Tip_Control	25983 non-null	object
37	Tire_Size	97638 non-null	object
38	Coupler Cystom	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 46	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

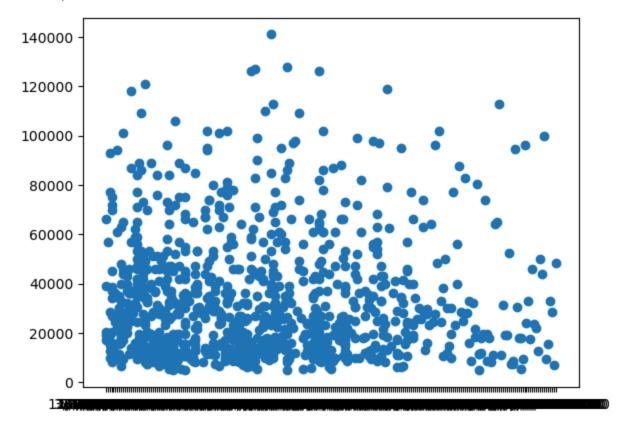
dtypes: float64(3), int64(5), object(45)
memory usage: 166.9+ MB

In [9]: df.isna().sum()

Out[9]:	SalesID	Θ
	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	210003
	state ProductCroup	0
	ProductGroup	0
	ProductGroupDesc	_
	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	
	**	

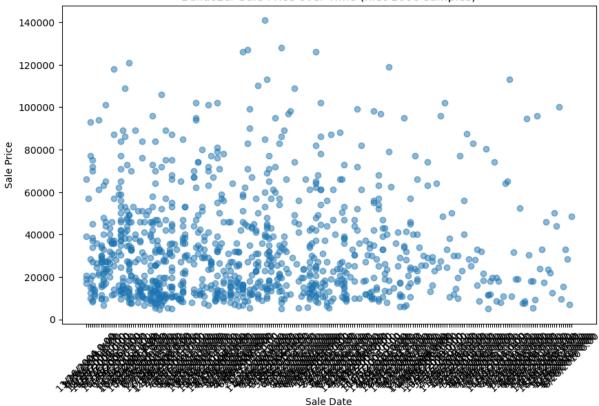
```
In [10]: fig , ax = plt.subplots()
ax.scatter(df["saledate"][:1000] , df["SalePrice"][:1000])
```

Out[10]: <matplotlib.collections.PathCollection at 0x25f8ed3e3c0>



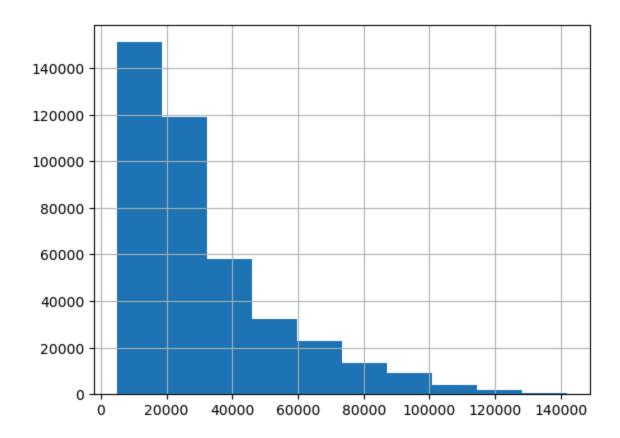
```
In [11]: fig, ax = plt.subplots(figsize=(10,6))
    ax.scatter(df["saledate"][:1000], df["SalePrice"][:1000], alpha=0.5)
    ax.set_xlabel("Sale Date")
    ax.set_ylabel("Sale Price")
    ax.set_title("Bulldozer Sale Price over Time (first 1000 samples)")
    plt.xticks(rotation=45) # rotate dates for readability
    plt.show()
```

#### Bulldozer Sale Price over Time (first 1000 samples)



```
In [12]: df.saledate
Out[12]: 0
                   11/16/2006 0:00
         1
                    3/26/2004 0:00
         2
                    2/26/2004 0:00
         3
                    5/19/2011 0:00
                    7/23/2009 0:00
         412693
                     3/7/2012 0:00
         412694
                    1/28/2012 0:00
         412695
                    1/28/2012 0:00
         412696
                     3/7/2012 0:00
                    1/28/2012 0:00
         412697
         Name: saledate, Length: 412698, dtype: object
In [13]: # Plot histogram
         df["SalePrice"].hist() # bins = number of intervals
```

Out[13]: <Axes: >



## **Prasing Data**

```
In [16]: df = pd.read_csv("data/TrainAndValid.csv" , low_memory= False , parse_dates=
In [38]: df
```

:		SalesID	SalePrice	MachineID	ModelID	datasource	auctioneerID	Y
	0	1139246	66000.0	999089	3157	121	3.0	
	1	1139248	57000.0	117657	77	121	3.0	
	2	1139249	10000.0	434808	7009	121	3.0	
	3	1139251	38500.0	1026470	332	121	3.0	
	4	1139253	11000.0	1057373	17311	121	3.0	
	412693	6333344	10000.0	1919201	21435	149	2.0	
	412694	6333345	10500.0	1882122	21436	149	2.0	
	412695	6333347	12500.0	1944213	21435	149	2.0	
	412696	6333348	10000.0	1794518	21435	149	2.0	
	412697	6333349	13000.0	1944743	21436	149	2.0	

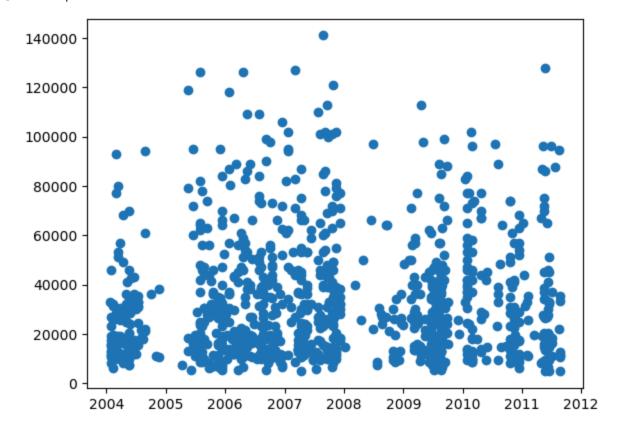
 $412698 \text{ rows} \times 53 \text{ columns}$ 

Out[38]

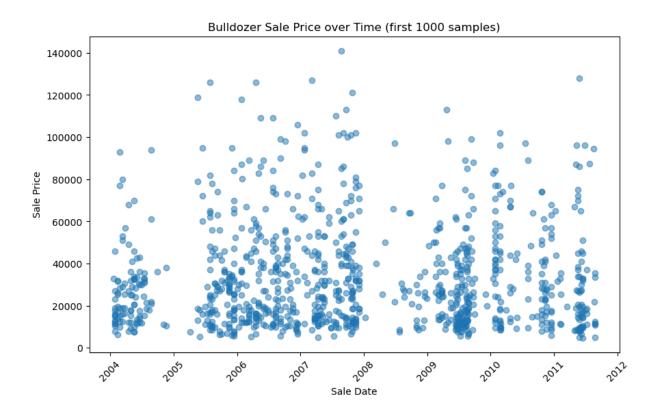
```
In [17]: df.saledate[:1000]
Out[17]: 0
                2006-11-16
          1
                2004-03-26
          2
                2004-02-26
          3
                2011-05-19
          4
                2009-07-23
          995
                2009-07-16
          996
                2007-06-14
          997
                2005-09-22
          998
                2005-07-28
          999
                2011-06-16
         Name: saledate, Length: 1000, dtype: datetime64[ns]
In [44]: df["saledate"]
```

```
2006-11-16
Out[44]: 0
          1
                   2004-03-26
          2
                   2004-02-26
          3
                   2011-05-19
                   2009-07-23
                      . . .
          412693
                   2012-03-07
          412694
                   2012-01-28
          412695
                   2012-01-28
          412696
                  2012-03-07
                   2012-01-28
          412697
          Name: saledate, Length: 412698, dtype: datetime64[ns]
In [18]: fig , ax = plt.subplots()
         ax.scatter(df["saledate"][:1000] , df["SalePrice"][:1000])
```

Out[18]: <matplotlib.collections.PathCollection at 0x25f922191d0>



```
In [19]: fig, ax = plt.subplots(figsize=(10,6))
    ax.scatter(df["saledate"][:1000], df["SalePrice"][:1000], alpha=0.5)
    ax.set_xlabel("Sale Date")
    ax.set_ylabel("Sale Price")
    ax.set_title("Bulldozer Sale Price over Time (first 1000 samples)")
    plt.xticks(rotation=45) # rotate dates for readability
    plt.show()
```



In [20]: df.head().T

Out[20]: 0 1 2 3

SalesID	1139246	1139248	1139249	1139251
SalePrice	66000.0	57000.0	10000.0	38500.0
MachinelD	999089	117657	434808	1026470
ModelID	3157	77	7009	332
datasource	121	121	121	121
auctioneerID	3.0	3.0	3.0	3.0
YearMade	2004	1996	2001	2001
MachineHoursCurrentMeter	68.0	4640.0	2838.0	3486.0
UsageBand	Low	Low	High	High
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
fiModelDesc	521D	950FII	226	PC120-6E
fiBaseModel	521	950	226	PC120
fiSecondaryDesc	D	F	NaN	NaN
fiModelSeries	NaN	II	NaN	-6E
fiModelDescriptor	NaN	NaN	NaN	NaN
ProductSize	NaN	Medium	NaN	Small
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
state	Alabama	North Carolina	New York	Texas
ProductGroup	WL	WL	SSL	TEX
ProductGroupDesc	Wheel Loader	Wheel Loader	Skid Steer Loaders	Track Excavators
Drive_System	NaN	NaN	NaN	NaN
Enclosure	EROPS w AC	EROPS w AC	OROPS	EROPS w AC
Forks	None or Unspecified	None or Unspecified	None or Unspecified	NaN
Pad_Type	NaN	NaN	NaN	NaN
Ride_Control	None or Unspecified	None or Unspecified	NaN	NaN
Stick	NaN	NaN	NaN	NaN
Transmission	NaN	NaN	NaN	NaN

	0	1	2	3
Turbocharged	NaN	NaN	NaN	NaN
Blade_Extension	NaN	NaN	NaN	NaN
Blade_Width	NaN	NaN	NaN	NaN
Enclosure_Type	NaN	NaN	NaN	NaN
Engine_Horsepower	NaN	NaN	NaN	NaN
Hydraulics	2 Valve	2 Valve	Auxiliary	2 Valve
Pushblock	NaN	NaN	NaN	NaN
Ripper	NaN	NaN	NaN	NaN
Scarifier	NaN	NaN	NaN	NaN
Tip_Control	NaN	NaN	NaN	NaN
Tire_Size	None or Unspecified	23.5	NaN	NaN
Coupler	None or Unspecified	None or Unspecified	None or Unspecified	None or Unspecified
Coupler_System	NaN	NaN	None or Unspecified	NaN
Grouser_Tracks	NaN	NaN	None or Unspecified	NaN
Hydraulics_Flow	NaN	NaN	Standard	NaN
Track_Type	NaN	NaN	NaN	NaN
Undercarriage_Pad_Width	NaN	NaN	NaN	NaN
Stick_Length	NaN	NaN	NaN	NaN
Thumb	NaN	NaN	NaN	NaN
Pattern_Changer	NaN	NaN	NaN	NaN
Grouser_Type	NaN	NaN	NaN	NaN
Backhoe_Mounting	NaN	NaN	NaN	NaN
Blade_Type	NaN	NaN	NaN	NaN
Travel_Controls	NaN	NaN	NaN	NaN
Differential_Type	Standard	Standard	NaN	NaN
Steering_Controls	Conventional	Conventional	NaN	NaN

## Sort Dataframe by Saledate

```
In [23]: df.sort_values(by=["saledate"] , inplace = True , ascending = True)
In [24]: df["saledate"].head(50)
```

```
Out[24]:
          205615
                    1989-01-17
          233186
                    1989-01-31
          142491
                    1989-01-31
          115536
                    1989-01-31
          92301
                    1989-01-31
          115892
                    1989-01-31
          134080
                    1989-01-31
          92294
                    1989-01-31
          31494
                    1989-01-31
          140922
                    1989-01-31
          66337
                    1989-01-31
          92531
                    1989-01-31
          82122
                    1989-01-31
          92256
                    1989-01-31
          145670
                    1989-01-31
          92780
                    1989-01-31
          238373
                    1989-01-31
          127132
                    1989-01-31
          115102
                    1989-01-31
          32317
                    1989-01-31
          238656
                    1989-01-31
          52508
                    1989-01-31
          127923
                    1989-01-31
          127521
                    1989-01-31
          152689
                    1989-01-31
          82165
                    1989-01-31
          78445
                    1989-01-31
          62665
                    1989-01-31
          113454
                    1989-01-31
          113547
                    1989-01-31
          28820
                    1989-01-31
          168619
                    1989-01-31
          115957
                    1989-01-31
          205782
                    1989-01-31
          114830
                    1989-01-31
          127735
                    1989-01-31
          78382
                    1989-01-31
          127674
                    1989-01-31
          28603
                    1989-01-31
          78278
                    1989-01-31
          231507
                    1989-01-31
          169757
                    1989-01-31
          92803
                    1989-01-31
          75832
                    1989-01-31
          88803
                    1989-01-31
          75378
                    1989-01-31
          169297
                    1989-01-31
          280078
                    1989-01-31
          140257
                    1989-01-31
          128751
                    1989-01-31
```

Name: saledate, dtype: datetime64[ns]

## Make a copy of orginal Data frame

In [25]:	<pre>df_tmp = df.copy()</pre>							
In [59]:	df_tmp							
Out[59]:		SalesID	SalePrice	MachineID	ModelID	datasource	auctioneerID	Y
	205615	1646770	9500.0	1126363	8434	132	18.0	
	274835	1821514	14000.0	1194089	10150	132	99.0	
	141296	1505138	50000.0	1473654	4139	132	99.0	
	212552	1671174	16000.0	1327630	8591	132	99.0	
	62755	1329056	22000.0	1336053	4089	132	99.0	
	410879	6302984	16000.0	1915521	5266	149	99.0	
	412476	6324811	6000.0	1919104	19330	149	99.0	
	411927	6313029	16000.0	1918416	17244	149	99.0	
	407124	6266251	55000.0	509560	3357	149	99.0	
	409203	6283635	34000.0	1869284	4701	149	99.0	

 $412698 \text{ rows} \times 53 \text{ columns}$ 

## add Datetime parameter for "SaleDate" column

```
In [26]: 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 [7]: df_tmp.head().T
```

Out[7]: 205615 274835 141296 212552

	203013	2/4833	141296	212552
SalesID	1646770	1821514	1505138	1671174
SalePrice	9500.0	14000.0	50000.0	16000.0
MachineID	1126363	1194089	1473654	1327630
ModelID	8434	10150	4139	8591
datasource	132	132	132	132
auctioneerID	18.0	99.0	99.0	99.0
YearMade	1974	1980	1978	1980
MachineHoursCurrentMeter	NaN	NaN	NaN	NaN
UsageBand	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
fiModelDesc	TD20	A66	D7G	A62
fiBaseModel	TD20	A66	D7	A62
fiSecondaryDesc	NaN	NaN	G	NaN
fiModelSeries	NaN	NaN	NaN	NaN
fiModelDescriptor	NaN	NaN	NaN	NaN
ProductSize	Medium	NaN	Large	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
state	Texas	Florida	Florida	Florida
ProductGroup	ПТ	WL	ПТ	WL
ProductGroupDesc	Track Type Tractors	Wheel Loader	Track Type Tractors	Wheel Loader
Drive_System	NaN	NaN	NaN	NaN
Enclosure	OROPS	OROPS	OROPS	EROPS
Forks	NaN	None or Unspecified	NaN	None or Unspecified
Pad_Type	NaN	NaN	NaN	NaN
Ride_Control	NaN	None or Unspecified	NaN	None or Unspecified
Stick	NaN	NaN	NaN	NaN
Transmission	Direct Drive	NaN	Standard	NaN

	205615	274835	141296	212552
Turbocharged	NaN	NaN	NaN	NaN
Blade_Extension	NaN	NaN	NaN	NaN
Blade_Width	NaN	NaN	NaN	NaN
Enclosure_Type	NaN	NaN	NaN	NaN
Engine_Horsepower	NaN	NaN	NaN	NaN
Hydraulics	2 Valve	2 Valve	2 Valve	2 Valve
Pushblock	NaN	NaN	NaN	NaN
Ripper	None or Unspecified	NaN	None or Unspecified	NaN
Scarifier	NaN	NaN	NaN	NaN
Tip_Control	NaN	NaN	NaN	NaN
Tire_Size	NaN	None or Unspecified	NaN	None or Unspecified
Coupler	NaN	None or Unspecified	NaN	None or Unspecified
Coupler_System	NaN	NaN	NaN	NaN
Grouser_Tracks	NaN	NaN	NaN	NaN
Hydraulics_Flow	NaN	NaN	NaN	NaN
Track_Type	NaN	NaN	NaN	NaN
Undercarriage_Pad_Width	NaN	NaN	NaN	NaN
Stick_Length	NaN	NaN	NaN	NaN
Thumb	NaN	NaN	NaN	NaN
Pattern_Changer	NaN	NaN	NaN	NaN
Grouser_Type	NaN	NaN	NaN	NaN
Backhoe_Mounting	None or Unspecified	NaN	None or Unspecified	NaN
Blade_Type	Straight	NaN	Straight	NaN
Travel_Controls	None or Unspecified	NaN	None or Unspecified	NaN
Differential_Type	NaN	Standard	NaN	Standard
Steering_Controls	NaN	Conventional	NaN	Conventional
saleyear	1989	1989	1989	1989
saleMonth	1	1	1	1
saleDay	17	31	31	31
saleDayoFWeek	1	1	1	1

	205615	274835	141296	212552
saleDayofyear	17	31	31	31

#### Now we going to remove sale date

```
In [27]: df tmp.drop("saledate" , axis = 1 , inplace = True)
In [28]: df tmp.columns
Out[28]: Index(['SalesID', 'SalePrice', 'MachineID', 'ModelID', 'datasource',
                  'auctioneerID', 'YearMade', 'MachineHoursCurrentMeter', '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', 'Scarifie
          r',
                  'Tip_Control', 'Tire_Size', 'Coupler', 'Coupler_System',
                  'Grouser Tracks', 'Hydraulics Flow', 'Track Type',
                  'Undercarriage Pad Width', 'Stick Length', 'Thumb', 'Pattern Change
          r',
                  'Grouser Type', 'Backhoe Mounting', 'Blade Type', 'Travel Controls',
                  'Differential Type', 'Steering Controls', 'saleyear', 'saleMonth',
                  'saleDay', 'saleDayoFWeek', 'saleDayofyear'],
                 dtype='object')
In [29]: # Check the values of different columns
          df tmp.state.value counts()
```

Out[29]:		67000
	Florida	67320
	Texas California	53110 29761
	Washington	16222
	Georgia	14633
	Maryland	13322
	Mississippi	13240
	Ohio ''	12369
	Illinois	11540
	Colorado	11529
	New Jersey	11156
	North Carolina	10636
	Tennessee	10298
	Alabama Pennsylvania	10292 10234
	South Carolina	9951
	Arizona	9364
	New York	8639
	Connecticut	8276
	Minnesota	7885
	Missouri	7178
	Nevada	6932
	Louisiana	6627
	Kentucky Maine	5351 5096
	Indiana	4124
	Arkansas	3933
	New Mexico	3631
	Utah	3046
	Unspecified	2801
	Wisconsin	2745
	New Hampshire	2738
	Virginia	2353
	Idaho	2025 1911
	Oregon Michigan	1831
	Wyoming	1672
	Montana	1336
	Iowa	1336
	Oklahoma	1326
	Nebraska	866
	West Virginia	840
	Kansas Delaware	667 510
	North Dakota	480
	Alaska	430
	Massachusetts	347
	Vermont	300
	South Dakota	244
	Hawaii	118
	Rhode Island	83
	Puerto Rico Washington DC	42 2
	Name: count, dtype	
	count, acypt	C. INCO-

## 5. Modelling

In [30]: from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor(n\_jobs = -1 , random\_state=42)

In [15]: **df** 

Out[15]:

	SalesID	SalePrice	MachineID	ModelID	datasource	auctioneerID	Y
205615	1646770	9500.0	1126363	8434	132	18.0	
274835	1821514	14000.0	1194089	10150	132	99.0	
141296	1505138	50000.0	1473654	4139	132	99.0	
212552	1671174	16000.0	1327630	8591	132	99.0	
62755	1329056	22000.0	1336053	4089	132	99.0	
410879	6302984	16000.0	1915521	5266	149	99.0	
412476	6324811	6000.0	1919104	19330	149	99.0	
411927	6313029	16000.0	1918416	17244	149	99.0	
407124	6266251	55000.0	509560	3357	149	99.0	
409203	6283635	34000.0	1869284	4701	149	99.0	

 $412698 \text{ rows} \times 53 \text{ columns}$ 

In [31]: df.info()

<class 'pandas.core.frame.DataFrame'>
Index: 412698 entries, 205615 to 409203
Data columns (total 53 columns):

Data	columns (total 53 columns	):	
#	Column	Non-Null Count	Dtype
0	SalesID	412698 non-null	int64
1	SalePrice	412698 non-null	
2	MachineID	412698 non-null	int64
3	ModelID	412698 non-null	int64
4	datasource	412698 non-null	int64
5	auctioneerID	392562 non-null	
6	YearMade	412698 non-null	int64
7	MachineHoursCurrentMeter	147504 non-null	
8	UsageBand	73670 non-null	
9	saledate	412698 non-null	datetime64[ns]
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		412698 non-null	_
	state DandwatCrawn		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	_	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
	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 50	Blade_Type Travel Centrals	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: datetime64[ns](1), float64(3), int64(5), object(44)

memory usage: 170.0+ MB

In [32]: df.isna().sum()

Out[32]:		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 Stick	259970
	Transmission	331602 224691
		331602
	Turbocharged 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	

## Convert String to categories

In [27]: df\_tmp.info()

<class 'pandas.core.frame.DataFrame'>
Index: 412698 entries, 205615 to 409203
Data columns (total 57 columns):

	columns (total 5/ columns		5.
#	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	
29	<del>_</del>	25983 non-null	object
30	Enclosure_Type		object
31	Engine_Horsepower Hydraulics	25983 non-null 330133 non-null	object
			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 int32
         53 saleMonth
                                      412698 non-null int32
                                      412698 non-null int32
         54 saleDay
         55 saleDayoFWeek
                                      412698 non-null int32
         56 saleDayofyear
                                      412698 non-null int32
        dtypes: float64(3), int32(5), int64(5), object(44)
        memory usage: 174.7+ MB
In [33]: pd.api.types.is string dtype(df tmp["UsageBand"])
Out[33]: False
In [34]: for label , content in df tmp.items():
             if pd.api.types.is string dtype(content):
                 print(label)
             #if pd.api.types.is_string_dtype(df_tmp())
        fiModelDesc
        fiBaseModel
        fiProductClassDesc
        state
        ProductGroup
        ProductGroupDesc
In [35]: for label ,content in df tmp.items():
             if pd.api.types.is object dtype(content):
                 df_tmp[label] = content.astype("category").cat.as_ordered()
In [36]:
          df tmp.info()
```

<class 'pandas.core.frame.DataFrame'>
Index: 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 int32
53 saleMonth 412698 non-null int32
54 saleDay 412698 non-null int32
55 saleDayoFWeek 412698 non-null int32
56 saleDayofyear 412698 non-null int32
dtypes: category(44), float64(3), int32(5), int64(5)
memory usage: 55.4 MB
```

```
In [37]: df tmp.state.cat.codes
Out[37]: 205615
                  43
         233186
                   8
         142491
                   8
         115536
                   8
         92301
                   8
         409901
                 4
         405777
                  4
         411889
                  4
         411890
                   4
         409203
                   4
         Length: 412698, dtype: int8
```

#### Thanks for categories

FIII Missing values

Fill numerical missing values first

```
In [38]: for label , content in df tmp.items():
             if pd.api.types.is numeric dtype(content):
                 print(df_tmp[label].isna().sum() , label)
        0 SalesID
        0 SalePrice
        0 MachineID
        0 ModelID
        0 datasource
        20136 auctioneerID
        0 YearMade
        265194 MachineHoursCurrentMeter
        0 saleyear
        0 saleMonth
        0 saleDay
        0 saleDayoFWeek
        0 saleDayofyear
In [61]: df tmp.ModelID
```

```
Out[61]: 205615
                   8434
         274835 10150
         141296
                   4139
         212552
                    8591
         62755
                    4089
                   . . .
         410879
                   5266
         412476 19330
                  17244
         411927
         407124
                   3357
         409203
                    4701
         Name: ModelID, Length: 412698, dtype: int64
In [39]: # 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 [40]: # Fill 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():
                     print(label)
        auctioneerID
        MachineHoursCurrentMeter
In [41]: # Fill 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():
                     print(label)
                     df_tmp[label + "_is_missing"] = pd.isnull(content)
                     df tmp[label] = content.fillna(content.median())
        auctioneerID
        MachineHoursCurrentMeter
In [42]: # Fill 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():
            print(label)
In [43]: df_tmp.auctioneerID_is_missing.value_counts()
```

Out[43]: auctioneerID is missing

False 392562 True 20136

Name: count, dtype: int64

#### Filling and turning categorical variables into numbers

```
In [44]: 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 [45]: # Turn categorical variables into numbers
         for label , content in df tmp.items():
             if not pd.api.types.is numeric dtype(content):
                 # Add binary column to indicate
                 df tmp[label+" is missing"] = pd.isnull(content)
                 df tmp[label] = pd.Categorical(content).codes+1
```

```
df_tmp.isna().sum()
In [46]:
Out[46]: SalesID
                                          0
                                          0
          SalePrice
         MachineID
                                          0
                                          0
         ModelID
          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
          Length: 103, dtype: int64
In [47]: df.isna().sum()
```

Out[47]:		0
	SalePrice	0
	MachineID	0
	ModelID	0 0
	datasource	20136
	auctioneerID YearMade	20130
	MachineHoursCurrentMeter	265194
		339028
	UsageBand 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 [48]: df tmp.head()
Out[48]:
                  SalesID
                           SalePrice MachineID ModelID datasource auctioneerID
         205615 1646770
                              9500.0
                                        1126363
                                                    8434
                                                                 132
                                                                               18.0
         274835 1821514
                             14000.0
                                        1194089
                                                   10150
                                                                 132
                                                                               99.0
                                        1473654
         141296 1505138
                             50000.0
                                                    4139
                                                                 132
                                                                              99.0
         212552 1671174
                             16000.0
                                        1327630
                                                    8591
                                                                 132
                                                                              99.0
                                                                 132
                                                                              99.0
          62755 1329056
                            22000.0
                                        1336053
                                                    4089
        5 \text{ rows} \times 103 \text{ columns}
In [51]: %%time
         model = RandomForestRegressor(n jobs = -1 , random state=42)
         model.fit(df_tmp.drop("SalePrice" , axis =1) ,df_tmp["SalePrice"])
        CPU times: total: 31min 4s
        Wall time: 3min 5s
Out[51]:
         RandomForestRegressor
         ▶ Parameters
In [52]: %time
         model.score(df tmp.drop("SalePrice" , axis =1) ,df tmp["SalePrice"])
        CPU times: total: 38.8 s
        Wall time: 4.1 s
Out[52]: 0.9875966080326709
         Spliting data into train/validation sets
In [53]: df_val = df_tmp[df_tmp.saleyear == 2012]
         df train = df tmp[df tmp.saleyear != 2012]
In [55]: len(df train) , len(df val)
Out[55]: (401125, 11573)
```

```
Out[55]: (401125, 11573)
In [56]: len(df_train) + len(df_val)
Out[56]: 412698
In [57]: x_train , y_train = df_train.drop("SalePrice" , axis = 1) , df_train.SalePri
In [58]: 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[58]: ((401125, 102), (401125,), (11573, 102), (11573,))
```

#### **Building and evaluation Funtion**

```
In [59]: # Create evaluation function
         from sklearn.metrics import mean squared log error , mean absolute error
         from sklearn.metrics import r2 score
         def rmsle(y test,y preds):
             Calculate root mean squard log error
             return np.sqrt(mean_squared_log_error(y_test , y_preds))
         # Create function to evaluate model on a few different levels
         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 R2" : r2_score(y_train , train preds),
                       "Valid R2" : r2 score(y valid , val preds)
             return scores
```

#### Testing our model on subset

```
%%time
         model = RandomForestRegressor(n jobs=-1, random state=42)
         model.fit(x_train, y_train)
In [60]: # CHnage max sample value
         model = RandomForestRegressor(n jobs=-1 , random state=42 , max samples = 1€
         model
```

```
Out[60]:
         RandomForestRegressor
         ▶ Parameters
In [61]: x train.shape[0]
Out[61]: 401125
In [62]: %%time
         model.fit(x_train , y_train)
       CPU times: total: 59.1 s
       Wall time: 6.07 s
Out[62]:
         RandomForestRegressor
         ▶ Parameters
In [63]: show scores(model)
Out[63]: {'Training MAE': 5548.995840324088,
          'Valid MAE': 7179.6961392897265,
          'Training RMSLE': np.float64(0.25737726780537257),
          'Valid RMSLE': np.float64(0.29404344200903443),
          'Training R2': 0.8610738743845617,
          'Valid R2': 0.8320179198265637}
In [64]: %time
         from sklearn.model selection import RandomizedSearchCV
         rf grid = {"n estimators"}
        CPU times: total: 0 ns
       Wall time: 31.2 µs
        Train a model with best hyparameters
In [65]: %time
         ideal model = RandomForestRegressor(n_estimators=40 , min_samples_leaf=1, mi
         ideal_model.fit(x_train , y_train)
        CPU times: total: 5min 19s
       Wall time: 32.5 s
```

Out[65]:

RandomForestRegressor

▶ Parameters

#### Make predictions on test data

#### Make predictions

```
"" test_preds = ideal_model.predict(test_df) ""
```

This has error because this is not same as the training set Now we are going to preprocess the data and make sure its same as ...

```
In [69]: def preprocess_data(test_df):
    """

Perform transformation on df and returns transformed df.
    """"

test_df["saleyear"] = test_df.saledate.dt.year
    test_df["saleMonth"] = test_df.saledate.dt.day
    test_df["saleDay"] = test_df.saledate.dt.day
    test_df["saleDayoFWeek"] = test_df.saledate.dt.dayofweek
    test_df["saleDayofyear"] = test_df.saledate.dt.dayofyear

test_df.drop("saledate" , axis =1 , inplace=True)'''

# Fill the numeric rows with median
    for label , content in test_df.items():
        if pd.api.types.is_numeric_dtype(content):
```

```
if pd.isnull(content).sum():
    print(label)
    test_df[label + "_is_missing"] = pd.isnull(content)
    test_df[label] = content.fillna(content.median())

#Filled categorical missing data and turned in numbers

if not pd.api.types.is_numeric_dtype(content):
    # Add binary column to indicate
    test_df[label+"_is_missing"] = pd.isnull(content)

    test_df[label] = pd.Categorical(content).codes+1

return test_df
```

```
In [70]: test_df.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12457 entries, 0 to 12456
Data columns (total 52 columns):

#	Column	Non-Null Count	Dtype
0	SalesID	12457 non-null	int64
1	MachineID	12457 non-null	int64
2	ModelID	12457 non-null	int64
3	datasource	12457 non-null	int64
4	auctioneerID	12457 non-null	int64
5	YearMade	12457 non-null	int64
6	MachineHoursCurrentMeter	2129 non-null	float64
7	UsageBand	1834 non-null	object
8	saledate	12457 non-null	datetime64[ns]
9	fiModelDesc	12457 non-null	object
10	fiBaseModel	12457 non-null	object
11		8482 non-null	-
12	fiSecondaryDesc fiModelSeries	2006 non-null	object
13			object
	fiModelDescriptor ProductSize	3024 non-null 6048 non-null	object
14			object
15	fiProductClassDesc	12457 non-null	object
16	state	12457 non-null	object
17	ProductGroup	12457 non-null	object
18	ProductGroupDesc	12457 non-null	object
19	Drive_System	2759 non-null	object
20	Enclosure	12455 non-null	object
21	Forks	6308 non-null	object
22	Pad_Type	2108 non-null	object
23	Ride_Control	4241 non-null	object
24	Stick	2108 non-null	object
25	Transmission	4818 non-null	object
26	Turbocharged	2108 non-null	object
27	Blade_Extension	651 non-null	object
28	Blade_Width	651 non-null	object
29	Enclosure_Type	651 non-null	object
30	Engine_Horsepower	651 non-null	object
31	Hydraulics	10315 non-null	object
32	Pushblock	651 non-null	object
33	Ripper	2704 non-null	object
34	Scarifier	651 non-null	object
35	Tip_Control	651 non-null	object
36	Tire_Size	2778 non-null	object
37	Coupler	7601 non-null	object
38	Coupler_System	2066 non-null	object
39	Grouser_Tracks	2066 non-null	object
40	Hydraulics_Flow	2066 non-null	object
41	Track_Type	3394 non-null	object
42	Undercarriage_Pad_Width	3398 non-null	object
43	Stick_Length	3394 non-null	object
44	Thumb	3395 non-null	object
45	Pattern_Changer	3394 non-null	object
46	Grouser_Type	3394 non-null	object
47	Backhoe_Mounting	2051 non-null	object
48	Blade_Type	2058 non-null	object
49	Travel_Controls	2058 non-null	object
50	Differential_Type	2129 non-null	object

51 Steering\_Controls 2129 non-null object

dtypes: datetime64[ns](1), float64(1), int64(6), object(44)

memory usage: 4.9+ MB

In [71]: preprocess\_data(test\_df)

MachineHoursCurrentMeter

-								
Out[71]:		SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	М
	0	1227829	1006309	3168	121	3	1999	
	1	1227844	1022817	7271	121	3	1000	
	2	1227847	1031560	22805	121	3	2004	
	3	1227848	56204	1269	121	3	2006	
	4	1227863	1053887	22312	121	3	2005	
	12452	6643171	2558317	21450	149	2	2008	
	12453	6643173	2558332	21434	149	2	2005	
	12454	6643184	2558342	21437	149	2	1000	
	12455	6643186	2558343	21437	149	2	2006	
	12456	6643196	2558346	21446	149	2	2008	

12457 rows × 98 columns

In [85]:	test_df				
----------	---------	--	--	--	--

Out[85]:		SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	М
	0	1227829	1006309	3168	121	False	1999	
	1	1227844	1022817	7271	121	False	1000	
	2	1227847	1031560	22805	121	False	2004	
	3	1227848	56204	1269	121	False	2006	
	4	1227863	1053887	22312	121	False	2005	
	12452	6643171	2558317	21450	149	False	2008	
	12453	6643173	2558332	21434	149	False	2005	
	12454	6643184	2558342	21437	149	False	1000	
	12455	6643186	2558343	21437	149	False	2006	
	12456	6643196	2558346	21446	149	False	2008	

12457 rows × 102 columns

In [72]:	<pre>test_df.isna().sum()</pre>										
Out[72]:	Sa	alesID			0						
		nchineID			0						
		odelID			0						
		atasource	· D		0						
	aı	ıctioneerI	.υ		0						
	Ra	ckhoe Mou	nting is mi		0						
			is missing	SSING	0						
			rols_is_mis:	sina	0						
		_	il Type is m		0						
			ontrols_is_m	-	0						
			dtype: int								
In [79]:	te	st_df.hea	d()								
Out[79]:		SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	Machir			
	0	1227829	1006309	3168	121	False	1999				
	1	1227844	1022817	7271	121	False	1000				
	2	1227847	1031560	22805	121	False	2004				

 $5 \text{ rows} \times 102 \text{ columns}$ 

1227848

1227863

<pre>In [58]: x_train.head()</pre>
------------------------------------

Out[58]:		SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	I
	205615	1646770	1126363	8434	132	18.0	1974	
	274835	1821514	1194089	10150	132	99.0	1980	
	141296	1505138	1473654	4139	132	99.0	1978	
	212552	1671174	1327630	8591	132	99.0	1980	
	62755	1329056	1336053	4089	132	99.0	1984	

False

False

5 rows × 102 columns

```
In [74]: # GOING TO FIND THE COLLUMN DIFFER
set(x_train.columns) - set(test_df.columns)
```

```
Out[74]: {'auctioneerID is missing',
           'saleDay',
           'saleDayoFWeek',
           'saleDayofyear',
           'saleMonth',
           'saleyear'}
In [75]: ## adjust df test to have aunctioneer id
         test_df["auctioneerID_is_missing"] = False
In [76]: len(x valid) , len(test df)
Out[76]: (11573, 12457)
In [76]: test df
Out[76]:
                 SalesID MachineID ModelID datasource auctioneerID YearMade M
              0 1227829
                             1006309
                                                                               1999
                                         3168
                                                       121
                                                                    False
              1 1227844
                             1022817
                                         7271
                                                                               1000
                                                       121
                                                                    False
              2 1227847
                             1031560
                                        22805
                                                       121
                                                                    False
                                                                               2004
              3 1227848
                               56204
                                         1269
                                                       121
                                                                    False
                                                                               2006
              4 1227863
                             1053887
                                        22312
                                                       121
                                                                    False
                                                                               2005
         12452 6643171
                             2558317
                                        21450
                                                       149
                                                                               2008
                                                                    False
         12453 6643173
                             2558332
                                        21434
                                                       149
                                                                    False
                                                                               2005
         12454 6643184
                             2558342
                                        21437
                                                       149
                                                                    False
                                                                               1000
         12455 6643186
                             2558343
                                        21437
                                                       149
                                                                    False
                                                                               2006
         12456 6643196
                             2558346
                                        21446
                                                       149
                                                                    False
                                                                               2008
```

 $12457 \text{ rows} \times 102 \text{ columns}$ 

### Make predictions on test data

test\_preds = ideal\_model.predict(test\_df)

```
In [77]: test_df = preprocess_data(test_df)
In [90]: test_df
```

Out[90]:		SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	M
	0	1227829	1006309	3168	121	False	1999	
	1	1227844	1022817	7271	121	False	1000	
	2	1227847	1031560	22805	121	False	2004	
	3	1227848	56204	1269	121	False	2006	
	4	1227863	1053887	22312	121	False	2005	
					•••			
	12452	6643171	2558317	21450	149	False	2008	
	12453	6643173	2558332	21434	149	False	2005	
	12454	6643184	2558342	21437	149	False	1000	
	12455	6643186	2558343	21437	149	False	2006	
	12456	6643196	2558346	21446	149	False	2008	

12457 rows × 102 columns

```
In [78]: # Preprocess test data
  test_df_proc = preprocess_data(test_df)

# Match the columns to training data
  test_df_proc = test_df_proc.reindex(columns=x_train.columns, fill_value=0)

# Now predict
  test_preds = ideal_model.predict(test_df_proc)
```

In [79]: len(test\_preds)

Out[79]: 12457

In [99]: test\_df\_proc

Out[99]:		SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	М
	0	1227829	1006309	3168	121	False	1999	
	1	1227844	1022817	7271	121	False	1000	
	2	1227847	1031560	22805	121	False	2004	
	3	1227848	56204	1269	121	False	2006	
	4	1227863	1053887	22312	121	False	2005	
	12452	6643171	2558317	21450	149	False	2008	
	12453	6643173	2558332	21434	149	False	2005	
	12454	6643184	2558342	21437	149	False	1000	
	12455	6643186	2558343	21437	149	False	2006	
	12456	6643196	2558346	21446	149	False	2008	
	12457 r	ows × 102	columns					

```
In [80]: # Format predictions into the same format

df_preds = pd.DataFrame()

df_preds["SalesID"] = test_df["SalesID"]

df_preds["SalesPrice"] = test_preds
```

In [105... df\_preds

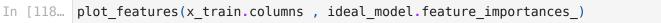
	<u> </u>		
Out[105		SalesID	SalesPrice
	0	1227829	17623.337125
	1	1227844	14566.296570
	2	1227847	46662.254410
	3	1227848	71305.266295
	4	1227863	61762.999424
	12452	66/2171	10160 995010

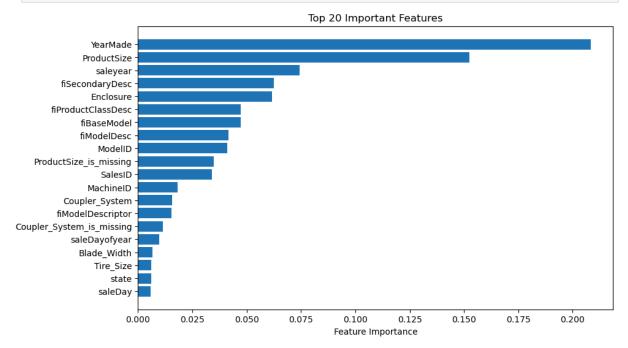
12452664317140469.88591012453664317312196.27761712454664318411964.85073312455664318616342.165338

**12456** 6643196 27119.990440

 $12457 \text{ rows} \times 2 \text{ columns}$ 

```
df preds.to csv("test prediction.csv" , index = False)
In [81]:
In [82]: len(ideal model.feature importances )
Out[82]: 102
In [83]:
         # Helper function for plotting feature importance
         def plot features(columns, importances, n=20):
             # Create a DataFrame with features and their importance
             df = (
                 pd.DataFrame({
                     "feature": columns,
                      "importance": importances
                  .sort values("importance", ascending=False)
                  .reset index(drop=True)
             )
             # Plot
             fig, ax = plt.subplots(figsize=(10, 6))
             ax.barh(df["feature"][:n][::-1], df["importance"][:n][::-1]) # horizont
             ax.set xlabel("Feature Importance")
             ax.set title(f"Top {n} Important Features")
             plt.show()
```





```
In [119... x_train.head()
```

Out[119		SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade I
	205615	1646770	1126363	8434	132	18.0	1974
	274835	1821514	1194089	10150	132	99.0	1980
	141296	1505138	1473654	4139	132	99.0	1978
	212552	1671174	1327630	8591	132	99.0	1980

 $5 \text{ rows} \times 102 \text{ columns}$ 

1329056

In [ ]:		

This notebook was converted with convert.ploomber.io

99.0