

Blue Book for Bulldozers

September 30, 2018

1 Blue Book for Bulldozers

```
In [64]: %load_ext autoreload
         %autoreload 2
         %matplotlib inline
```

The autoreload extension is already loaded. To reload it, use:

```
%reload_ext autoreload
```

```
In [65]: from fastai.imports import *
         from fastai.structured import *

         from pandas_summary import DataFrameSummary
         from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
         from IPython.display import display

         from sklearn import metrics
```

```
In [66]: # point path to data
         PATH = "data/bulldozers/"
```

```
In [67]: # use bash command to list out data
         !ls {PATH}
```

Data Dictionary.xlsx	random_forest_benchmark_test.csv	Train.csv
Machine_Appendix.csv	Test.csv	Valid.csv
median_benchmark.csv	tmp	ValidSolution.csv
models	TrainAndValid.csv	

```
In [68]: # notice parse_dates, this is an important step when you have a
         # date column thats not already split into its constituent parts
         df_raw = pd.read_csv(f'{PATH}Train.csv', low_memory=False,
                             parse_dates=["saledate"])
```

In any sort of data science work, it's **important to look at your data**, to make sure you understand the format, how it's stored, what type of values it holds, etc. Even if you've read descriptions about your data, the actual data may not be what you expect.

```
In [69]: def display_all(df):
         with pd.option_context("display.max_rows", 1000, "display.max_columns", 1000):
             display(df)
```

```
In [70]: display_all(df_raw.tail().T)
```

	401120	\
SalesID	6333336	
SalePrice	10500	
MachineID	1840702	
ModelID	21439	
datasource	149	
auctioneerID	1	
YearMade	2005	
MachineHoursCurrentMeter	NaN	
UsageBand	NaN	
saledate	2011-11-02 00:00:00	
fiModelDesc	35NX2	
fiBaseModel	35	
fiSecondaryDesc	NX	
fiModelSeries	2	
fiModelDescriptor	NaN	
ProductSize	Mini	
fiProductClassDesc	Hydraulic Excavator, Track - 3.0 to 4.0 Metric...	
state	Maryland	
ProductGroup	TEX	
ProductGroupDesc	Track Excavators	
Drive_System	NaN	
Enclosure	EROPS	
Forks	NaN	
Pad_Type	NaN	
Ride_Control	NaN	
Stick	NaN	
Transmission	NaN	
Turbocharged	NaN	
Blade_Extension	NaN	
Blade_Width	NaN	
Enclosure_Type	NaN	
Engine_Horsepower	NaN	
Hydraulics	Auxiliary	
Pushblock	NaN	
Ripper	NaN	
Scarifier	NaN	
Tip_Control	NaN	
Tire_Size	NaN	
Coupler	None or Unspecified	
Coupler_System	NaN	
Grouser_Tracks	NaN	

Hydraulics_Flow	NaN
Track_Type	Steel
Undercarriage_Pad_Width	None or Unspecified
Stick_Length	None or Unspecified
Thumb	None or Unspecified
Pattern_Changer	None or Unspecified
Grouser_Type	Double
Backhoe_Mounting	NaN
Blade_Type	NaN
Travel_Controls	NaN
Differential_Type	NaN
Steering_Controls	NaN
SalesID	401121 \
SalePrice	6333337
MachineID	11000
ModelID	1830472
datasource	21439
auctioneerID	149
YearMade	1
MachineHoursCurrentMeter	2005
UsageBand	NaN
saledate	NaN
fiModelDesc	2011-11-02 00:00:00
fiBaseModel	35NX2
fiSecondaryDesc	35
fiModelSeries	NX
fiModelDescriptor	2
ProductSize	NaN
fiProductClassDesc	Mini
state	Hydraulic Excavator, Track - 3.0 to 4.0 Metric...
ProductGroup	Maryland
ProductGroupDesc	TEX
Drive_System	Track Excavators
Enclosure	NaN
Forks	EROPS
Pad_Type	NaN
Ride_Control	NaN
Stick	NaN
Transmission	NaN
Turbocharged	NaN
Blade_Extension	NaN
Blade_Width	NaN
Enclosure_Type	NaN
Engine_Horsepower	NaN
Hydraulics	Standard
Pushblock	NaN

Ripper	NaN
Scarifier	NaN
Tip_Control	NaN
Tire_Size	NaN
Coupler	None or Unspecified
Coupler_System	NaN
Grouser_Tracks	NaN
Hydraulics_Flow	NaN
Track_Type	Steel
Undercarriage_Pad_Width	None or Unspecified
Stick_Length	None or Unspecified
Thumb	None or Unspecified
Pattern_Changer	None or Unspecified
Grouser_Type	Double
Backhoe_Mounting	NaN
Blade_Type	NaN
Travel_Controls	NaN
Differential_Type	NaN
Steering_Controls	NaN

	401122	\
SalesID	6333338	
SalePrice	11500	
MachineID	1887659	
ModelID	21439	
datasource	149	
auctioneerID	1	
YearMade	2005	
MachineHoursCurrentMeter	NaN	
UsageBand	NaN	
saledate	2011-11-02 00:00:00	
fiModelDesc	35NX2	
fiBaseModel	35	
fiSecondaryDesc	NX	
fiModelSeries	2	
fiModelDescriptor	NaN	
ProductSize	Mini	
fiProductClassDesc	Hydraulic Excavator, Track - 3.0 to 4.0 Metric...	
state	Maryland	
ProductGroup	TEX	
ProductGroupDesc	Track Excavators	
Drive_System	NaN	
Enclosure	EROPS	
Forks	NaN	
Pad_Type	NaN	
Ride_Control	NaN	
Stick	NaN	
Transmission	NaN	

Turbocharged	NaN
Blade_Extension	NaN
Blade_Width	NaN
Enclosure_Type	NaN
Engine_Horsepower	NaN
Hydraulics	Auxiliary
Pushblock	NaN
Ripper	NaN
Scarifier	NaN
Tip_Control	NaN
Tire_Size	NaN
Coupler	None or Unspecified
Coupler_System	NaN
Grouser_Tracks	NaN
Hydraulics_Flow	NaN
Track_Type	Steel
Undercarriage_Pad_Width	None or Unspecified
Stick_Length	None or Unspecified
Thumb	None or Unspecified
Pattern_Changer	None or Unspecified
Grouser_Type	Double
Backhoe_Mounting	NaN
Blade_Type	NaN
Travel_Controls	NaN
Differential_Type	NaN
Steering_Controls	NaN
SalesID	401123 \
SalePrice	6333341
MachineID	9000
ModelID	1903570
datasource	21435
auctioneerID	149
YearMade	2
MachineHoursCurrentMeter	2005
UsageBand	NaN
saledate	NaN
fiModelDesc	2011-10-25 00:00:00
fiBaseModel	30NX
fiSecondaryDesc	30
fiModelSeries	NX
fiModelDescriptor	NaN
ProductSize	NaN
fiProductClassDesc	Mini
state	Hydraulic Excavator, Track - 2.0 to 3.0 Metric...
ProductGroup	Florida
ProductGroupDesc	TEX
	Track Excavators

Drive_System	NaN
Enclosure	EROPS
Forks	NaN
Pad_Type	NaN
Ride_Control	NaN
Stick	NaN
Transmission	NaN
Turbocharged	NaN
Blade_Extension	NaN
Blade_Width	NaN
Enclosure_Type	NaN
Engine_Horsepower	NaN
Hydraulics	Standard
Pushblock	NaN
Ripper	NaN
Scarifier	NaN
Tip_Control	NaN
Tire_Size	NaN
Coupler	None or Unspecified
Coupler_System	NaN
Grouser_Tracks	NaN
Hydraulics_Flow	NaN
Track_Type	Steel
Undercarriage_Pad_Width	None or Unspecified
Stick_Length	None or Unspecified
Thumb	None or Unspecified
Pattern_Changer	None or Unspecified
Grouser_Type	Double
Backhoe_Mounting	NaN
Blade_Type	NaN
Travel_Controls	NaN
Differential_Type	NaN
Steering_Controls	NaN
	401124
SalesID	6333342
SalePrice	7750
MachineID	1926965
ModelID	21435
datasource	149
auctioneerID	2
YearMade	2005
MachineHoursCurrentMeter	NaN
UsageBand	NaN
saledate	2011-10-25 00:00:00
fiModelDesc	30NX
fiBaseModel	30
fiSecondaryDesc	NX

fiModelSeries	NaN
fiModelDescriptor	NaN
ProductSize	Mini
fiProductClassDesc	Hydraulic Excavator, Track - 2.0 to 3.0 Metric...
state	Florida
ProductGroup	TEX
ProductGroupDesc	Track Excavators
Drive_System	NaN
Enclosure	EROPS
Forks	NaN
Pad_Type	NaN
Ride_Control	NaN
Stick	NaN
Transmission	NaN
Turbocharged	NaN
Blade_Extension	NaN
Blade_Width	NaN
Enclosure_Type	NaN
Engine_Horsepower	NaN
Hydraulics	Standard
Pushblock	NaN
Ripper	NaN
Scarifier	NaN
Tip_Control	NaN
Tire_Size	NaN
Coupler	None or Unspecified
Coupler_System	NaN
Grouser_Tracks	NaN
Hydraulics_Flow	NaN
Track_Type	Steel
Undercarriage_Pad_Width	None or Unspecified
Stick_Length	None or Unspecified
Thumb	None or Unspecified
Pattern_Changer	None or Unspecified
Grouser_Type	Double
Backhoe_Mounting	NaN
Blade_Type	NaN
Travel_Controls	NaN
Differential_Type	NaN
Steering_Controls	NaN

```
In [71]: # the function above is important because if you notice
         # this option won't show every column
         df_raw
```

```
Out[71]:      SalesID  SalePrice  MachineID  ModelID  datasource  auctioneerID  \
0         1139246      66000      999089      3157          121          3.0
```

1	1139248	57000	117657	77	121	3.0
2	1139249	10000	434808	7009	121	3.0
3	1139251	38500	1026470	332	121	3.0
4	1139253	11000	1057373	17311	121	3.0
5	1139255	26500	1001274	4605	121	3.0
6	1139256	21000	772701	1937	121	3.0
7	1139261	27000	902002	3539	121	3.0
8	1139272	21500	1036251	36003	121	3.0
9	1139275	65000	1016474	3883	121	3.0
10	1139278	24000	1024998	4605	121	3.0
11	1139282	22500	319906	5255	121	3.0
12	1139283	36000	1052214	2232	121	3.0
13	1139284	30500	1068082	3542	121	3.0
14	1139290	28000	1058450	5162	121	3.0
15	1139291	19000	1004810	4604	121	3.0
16	1139292	13500	1026973	9510	121	3.0
17	1139299	9500	1002713	21442	121	3.0
18	1139301	12500	125790	7040	121	3.0
19	1139304	11500	1011914	3177	121	3.0
20	1139311	41000	1014135	8867	121	3.0
21	1139333	34500	999192	3350	121	3.0
22	1139344	26000	1044500	7040	121	3.0
23	1139346	73000	821452	85	121	3.0
24	1139348	33000	294562	3542	121	3.0
25	1139351	12500	833838	7009	121	3.0
26	1139354	15500	565440	7040	121	3.0
27	1139356	53000	1004127	25458	121	3.0
28	1139357	46000	44800	19167	121	3.0
29	1139358	89000	1018076	1333	121	3.0
...
401095	6333259	10500	1872639	21437	149	1.0
401096	6333260	10000	1816341	21437	149	2.0
401097	6333261	8500	1843949	21437	149	1.0
401098	6333262	10500	1791341	21437	149	2.0
401099	6333263	11000	1833174	21437	149	1.0
401100	6333264	10500	1791370	21437	149	2.0
401101	6333270	10000	1799208	21437	149	1.0
401102	6333272	10500	1927142	21437	149	2.0
401103	6333273	12500	1789856	21437	149	2.0
401104	6333275	10500	1924623	21437	149	2.0
401105	6333276	10000	1835350	21437	149	2.0
401106	6333278	10500	1944702	21437	149	2.0
401107	6333279	12500	1866563	21437	149	2.0
401108	6333280	10500	1851633	21437	149	2.0
401109	6333281	10500	1798958	21437	149	2.0
401110	6333282	10500	1878866	21437	149	2.0
401111	6333283	10000	1874235	21437	149	2.0
401112	6333284	10500	1887654	21437	149	2.0

401113	6333285	10500	1817165	21437	149	2.0
401114	6333287	12500	1918242	21437	149	2.0
401115	6333290	10000	1843374	21437	149	2.0
401116	6333302	8500	1825337	21437	149	2.0
401117	6333307	10000	1821747	21437	149	2.0
401118	6333311	9500	1828862	21437	149	2.0
401119	6333335	8500	1798293	21435	149	2.0
401120	6333336	10500	1840702	21439	149	1.0
401121	6333337	11000	1830472	21439	149	1.0
401122	6333338	11500	1887659	21439	149	1.0
401123	6333341	9000	1903570	21435	149	2.0
401124	6333342	7750	1926965	21435	149	2.0

	YearMade	MachineHours	CurrentMeter	UsageBand	saledate	\
0	2004		68.0	Low	2006-11-16	
1	1996		4640.0	Low	2004-03-26	
2	2001		2838.0	High	2004-02-26	
3	2001		3486.0	High	2011-05-19	
4	2007		722.0	Medium	2009-07-23	
5	2004		508.0	Low	2008-12-18	
6	1993		11540.0	High	2004-08-26	
7	2001		4883.0	High	2005-11-17	
8	2008		302.0	Low	2009-08-27	
9	1000		20700.0	Medium	2007-08-09	
10	2004		1414.0	Medium	2008-08-21	
11	1998		2764.0	Low	2006-08-24	
12	1998		0.0	NaN	2005-10-20	
13	2001		1921.0	Medium	2006-01-26	
14	2004		320.0	Low	2006-01-03	
15	1999		2450.0	Medium	2006-11-16	
16	1999		1972.0	Low	2007-06-14	
17	2003		0.0	NaN	2010-01-28	
18	2001		994.0	Low	2006-03-09	
19	1991		8005.0	Medium	2005-11-17	
20	2000		3259.0	Medium	2006-05-18	
21	1000		16328.0	Medium	2006-10-19	
22	2005		109.0	Low	2007-10-25	
23	1996		17033.0	High	2006-10-19	
24	2001		1877.0	Medium	2004-05-20	
25	2003		1028.0	Medium	2006-03-09	
26	2003		356.0	Low	2006-03-09	
27	2000		0.0	NaN	2007-02-22	
28	2004		904.0	Low	2007-08-09	
29	1998		10466.0	Medium	2006-06-01	
...	
401095	2003		NaN	NaN	2011-12-14	
401096	2004		NaN	NaN	2011-09-15	
401097	2005		NaN	NaN	2011-10-28	

401098	2004	NaN	NaN 2011-08-16
401099	2004	NaN	NaN 2011-12-14
401100	2004	NaN	NaN 2011-08-16
401101	2004	NaN	NaN 2011-12-14
401102	2005	NaN	NaN 2011-08-16
401103	2005	NaN	NaN 2011-09-15
401104	2005	NaN	NaN 2011-08-16
401105	2005	NaN	NaN 2011-10-25
401106	2005	NaN	NaN 2011-08-16
401107	2005	NaN	NaN 2011-09-15
401108	2005	NaN	NaN 2011-08-16
401109	2005	NaN	NaN 2011-08-16
401110	2005	NaN	NaN 2011-09-15
401111	2005	NaN	NaN 2011-10-25
401112	2005	NaN	NaN 2011-10-25
401113	2005	NaN	NaN 2011-10-25
401114	2005	NaN	NaN 2011-11-15
401115	2005	NaN	NaN 2011-10-25
401116	2005	NaN	NaN 2011-10-25
401117	2005	NaN	NaN 2011-10-25
401118	2006	NaN	NaN 2011-10-25
401119	2005	NaN	NaN 2011-10-25
401120	2005	NaN	NaN 2011-11-02
401121	2005	NaN	NaN 2011-11-02
401122	2005	NaN	NaN 2011-11-02
401123	2005	NaN	NaN 2011-10-25
401124	2005	NaN	NaN 2011-10-25

	...	Undercarriage_Pad_Width	Stick_Length \
0	...	NaN	NaN
1	...	NaN	NaN
2	...	NaN	NaN
3	...	NaN	NaN
4	...	NaN	NaN
5	...	NaN	NaN
6	...	None or Unspecified	None or Unspecified
7	...	NaN	NaN
8	...	None or Unspecified	None or Unspecified
9	...	NaN	NaN
10	...	NaN	NaN
11	...	NaN	NaN
12	...	None or Unspecified	11' 0"
13	...	NaN	NaN
14	...	NaN	NaN
15	...	NaN	NaN
16	...	None or Unspecified	None or Unspecified
17	...	16 inch	None or Unspecified
18	...	None or Unspecified	None or Unspecified

19	...	NaN	NaN
20	...	32 inch	None or Unspecified
21	...	NaN	NaN
22	...	None or Unspecified	None or Unspecified
23	...	NaN	NaN
24	...	NaN	NaN
25	...	NaN	NaN
26	...	None or Unspecified	None or Unspecified
27	...	None or Unspecified	None or Unspecified
28	...	NaN	NaN
29	...	None or Unspecified	15' 9"
...
401095	...	None or Unspecified	None or Unspecified
401096	...	None or Unspecified	None or Unspecified
401097	...	None or Unspecified	None or Unspecified
401098	...	None or Unspecified	None or Unspecified
401099	...	None or Unspecified	None or Unspecified
401100	...	None or Unspecified	None or Unspecified
401101	...	None or Unspecified	None or Unspecified
401102	...	None or Unspecified	None or Unspecified
401103	...	None or Unspecified	None or Unspecified
401104	...	None or Unspecified	None or Unspecified
401105	...	None or Unspecified	None or Unspecified
401106	...	None or Unspecified	None or Unspecified
401107	...	None or Unspecified	None or Unspecified
401108	...	None or Unspecified	None or Unspecified
401109	...	None or Unspecified	None or Unspecified
401110	...	None or Unspecified	None or Unspecified
401111	...	None or Unspecified	None or Unspecified
401112	...	None or Unspecified	None or Unspecified
401113	...	None or Unspecified	None or Unspecified
401114	...	None or Unspecified	None or Unspecified
401115	...	None or Unspecified	None or Unspecified
401116	...	None or Unspecified	None or Unspecified
401117	...	None or Unspecified	None or Unspecified
401118	...	None or Unspecified	None or Unspecified
401119	...	None or Unspecified	None or Unspecified
401120	...	None or Unspecified	None or Unspecified
401121	...	None or Unspecified	None or Unspecified
401122	...	None or Unspecified	None or Unspecified
401123	...	None or Unspecified	None or Unspecified
401124	...	None or Unspecified	None or Unspecified

	Thumb	Pattern_Changer	Grouser_Type	\
0	NaN	NaN	NaN	
1	NaN	NaN	NaN	
2	NaN	NaN	NaN	
3	NaN	NaN	NaN	

4		NaN	NaN	NaN
5		NaN	NaN	NaN
6	None or Unspecified	None or Unspecified		Double
7		NaN	NaN	NaN
8	None or Unspecified	None or Unspecified		Double
9		NaN	NaN	NaN
10		NaN	NaN	NaN
11		NaN	NaN	NaN
12	None or Unspecified	None or Unspecified		Double
13		NaN	NaN	NaN
14		NaN	NaN	NaN
15		NaN	NaN	NaN
16	None or Unspecified	None or Unspecified		Double
17	None or Unspecified	None or Unspecified		Double
18	None or Unspecified		Yes	Double
19		NaN	NaN	NaN
20	None or Unspecified	None or Unspecified		Double
21		NaN	NaN	NaN
22	None or Unspecified	None or Unspecified		Double
23		NaN	NaN	NaN
24		NaN	NaN	NaN
25		NaN	NaN	NaN
26	None or Unspecified		Yes	Double
27	None or Unspecified	None or Unspecified		Double
28		NaN	NaN	NaN
29	None or Unspecified		Yes	Double
...	
401095	None or Unspecified	None or Unspecified		Double
401096	None or Unspecified	None or Unspecified		Double
401097	None or Unspecified	None or Unspecified		Double
401098	None or Unspecified	None or Unspecified		Double
401099	None or Unspecified	None or Unspecified		Double
401100	None or Unspecified	None or Unspecified		Double
401101	None or Unspecified	None or Unspecified		Double
401102	None or Unspecified	None or Unspecified		Double
401103	None or Unspecified	None or Unspecified		Double
401104	None or Unspecified	None or Unspecified		Double
401105	None or Unspecified	None or Unspecified		Double
401106	None or Unspecified	None or Unspecified		Double
401107	None or Unspecified	None or Unspecified		Double
401108	None or Unspecified	None or Unspecified		Double
401109	None or Unspecified	None or Unspecified		Double
401110	None or Unspecified	None or Unspecified		Double
401111	None or Unspecified	None or Unspecified		Double
401112	None or Unspecified	None or Unspecified		Double
401113	None or Unspecified	None or Unspecified		Double
401114	None or Unspecified	None or Unspecified		Double
401115	None or Unspecified	None or Unspecified		Double

401116	None or Unspecified	None or Unspecified	Double
401117	None or Unspecified	None or Unspecified	Double
401118	None or Unspecified	None or Unspecified	Double
401119	None or Unspecified	None or Unspecified	Double
401120	None or Unspecified	None or Unspecified	Double
401121	None or Unspecified	None or Unspecified	Double
401122	None or Unspecified	None or Unspecified	Double
401123	None or Unspecified	None or Unspecified	Double
401124	None or Unspecified	None or Unspecified	Double

	Backhoe_Mounting	Blade_Type	Travel_Controls	Differential_Type \
0	NaN	NaN	NaN	Standard
1	NaN	NaN	NaN	Standard
2	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN
5	NaN	NaN	NaN	NaN
6	NaN	NaN	NaN	NaN
7	NaN	NaN	NaN	NaN
8	NaN	NaN	NaN	NaN
9	NaN	NaN	NaN	Standard
10	NaN	NaN	NaN	NaN
11	None or Unspecified	PAT	None or Unspecified	NaN
12	NaN	NaN	NaN	NaN
13	NaN	NaN	NaN	NaN
14	NaN	NaN	NaN	NaN
15	NaN	NaN	NaN	NaN
16	NaN	NaN	NaN	NaN
17	NaN	NaN	NaN	NaN
18	NaN	NaN	NaN	NaN
19	NaN	NaN	NaN	NaN
20	NaN	NaN	NaN	NaN
21	NaN	NaN	NaN	NaN
22	NaN	NaN	NaN	NaN
23	NaN	NaN	NaN	Standard
24	NaN	NaN	NaN	NaN
25	NaN	NaN	NaN	NaN
26	NaN	NaN	NaN	NaN
27	NaN	NaN	NaN	NaN
28	NaN	NaN	NaN	NaN
29	NaN	NaN	NaN	NaN
...
401095	NaN	NaN	NaN	NaN
401096	NaN	NaN	NaN	NaN
401097	NaN	NaN	NaN	NaN
401098	NaN	NaN	NaN	NaN
401099	NaN	NaN	NaN	NaN
401100	NaN	NaN	NaN	NaN

401101	NaN	NaN	NaN	NaN
401102	NaN	NaN	NaN	NaN
401103	NaN	NaN	NaN	NaN
401104	NaN	NaN	NaN	NaN
401105	NaN	NaN	NaN	NaN
401106	NaN	NaN	NaN	NaN
401107	NaN	NaN	NaN	NaN
401108	NaN	NaN	NaN	NaN
401109	NaN	NaN	NaN	NaN
401110	NaN	NaN	NaN	NaN
401111	NaN	NaN	NaN	NaN
401112	NaN	NaN	NaN	NaN
401113	NaN	NaN	NaN	NaN
401114	NaN	NaN	NaN	NaN
401115	NaN	NaN	NaN	NaN
401116	NaN	NaN	NaN	NaN
401117	NaN	NaN	NaN	NaN
401118	NaN	NaN	NaN	NaN
401119	NaN	NaN	NaN	NaN
401120	NaN	NaN	NaN	NaN
401121	NaN	NaN	NaN	NaN
401122	NaN	NaN	NaN	NaN
401123	NaN	NaN	NaN	NaN
401124	NaN	NaN	NaN	NaN

	Steering_Controls
0	Conventional
1	Conventional
2	NaN
3	NaN
4	NaN
5	NaN
6	NaN
7	NaN
8	NaN
9	Conventional
10	NaN
11	NaN
12	NaN
13	NaN
14	NaN
15	NaN
16	NaN
17	NaN
18	NaN
19	NaN
20	NaN
21	NaN

22	NaN
23	Conventional
24	NaN
25	NaN
26	NaN
27	NaN
28	NaN
29	NaN
...	...
401095	NaN
401096	NaN
401097	NaN
401098	NaN
401099	NaN
401100	NaN
401101	NaN
401102	NaN
401103	NaN
401104	NaN
401105	NaN
401106	NaN
401107	NaN
401108	NaN
401109	NaN
401110	NaN
401111	NaN
401112	NaN
401113	NaN
401114	NaN
401115	NaN
401116	NaN
401117	NaN
401118	NaN
401119	NaN
401120	NaN
401121	NaN
401122	NaN
401123	NaN
401124	NaN

[401125 rows x 53 columns]

```
In [72]: display_all(df_raw.describe(include='all').T)
```

	count	unique	\
SalesID	401125	NaN	
SalePrice	401125	NaN	
MachineID	401125	NaN	

ModelID	401125	NaN
datasource	401125	NaN
auctioneerID	380989	NaN
YearMade	401125	NaN
MachineHoursCurrentMeter	142765	NaN
UsageBand	69639	3
saledate	401125	3919
fiModelDesc	401125	4999
fiBaseModel	401125	1950
fiSecondaryDesc	263934	175
fiModelSeries	56908	122
fiModelDescriptor	71919	139
ProductSize	190350	6
fiProductClassDesc	401125	74
state	401125	53
ProductGroup	401125	6
ProductGroupDesc	401125	6
Drive_System	104361	4
Enclosure	400800	6
Forks	192077	2
Pad_Type	79134	4
Ride_Control	148606	3
Stick	79134	2
Transmission	183230	8
Turbocharged	79134	2
Blade_Extension	25219	2
Blade_Width	25219	6
Enclosure_Type	25219	3
Engine_Horsepower	25219	2
Hydraulics	320570	12
Pushblock	25219	2
Ripper	104137	4
Scarifier	25230	2
Tip_Control	25219	3
Tire_Size	94718	17
Coupler	213952	3
Coupler_System	43458	2
Grouser_Tracks	43362	2
Hydraulics_Flow	43362	3
Track_Type	99153	2
Undercarriage_Pad_Width	99872	19
Stick_Length	99218	29
Thumb	99288	3
Pattern_Changer	99218	3
Grouser_Type	99153	3
Backhoe_Mounting	78672	2
Blade_Type	79833	10
Travel_Controls	79834	7

Differential_Type	69411	4
Steering_Controls	69369	5

			top \
SalesID			NaN
SalePrice			NaN
MachineID			NaN
ModelID			NaN
datasource			NaN
auctioneerID			NaN
YearMade			NaN
MachineHoursCurrentMeter			NaN
UsageBand			Medium
saledate		2009-02-16 00:00:00	
fiModelDesc			310G
fiBaseModel			580
fiSecondaryDesc			C
fiModelSeries			II
fiModelDescriptor			L
ProductSize			Medium
fiProductClassDesc	Backhoe Loader - 14.0 to 15.0 Ft Standard Digg...		
state			Florida
ProductGroup			TEX
ProductGroupDesc			Track Excavators
Drive_System			Two Wheel Drive
Enclosure			OROPS
Forks			None or Unspecified
Pad_Type			None or Unspecified
Ride_Control			No
Stick			Standard
Transmission			Standard
Turbocharged			None or Unspecified
Blade_Extension			None or Unspecified
Blade_Width			14'
Enclosure_Type			None or Unspecified
Engine_Horsepower			No
Hydraulics			2 Valve
Pushblock			None or Unspecified
Ripper			None or Unspecified
Scarifier			None or Unspecified
Tip_Control			None or Unspecified
Tire_Size			None or Unspecified
Coupler			None or Unspecified
Coupler_System			None or Unspecified
Grouser_Tracks			None or Unspecified
Hydraulics_Flow			Standard
Track_Type			Steel
Undercarriage_Pad_Width			None or Unspecified

Stick_Length	None or Unspecified
Thumb	None or Unspecified
Pattern_Changer	None or Unspecified
Grouser_Type	Double
Backhoe_Mounting	None or Unspecified
Blade_Type	PAT
Travel_Controls	None or Unspecified
Differential_Type	Standard
Steering_Controls	Conventional

	freq	first	last \
SalesID	NaN	NaN	NaN
SalePrice	NaN	NaN	NaN
MachineID	NaN	NaN	NaN
ModelID	NaN	NaN	NaN
datasource	NaN	NaN	NaN
auctioneerID	NaN	NaN	NaN
YearMade	NaN	NaN	NaN
MachineHoursCurrentMeter	NaN	NaN	NaN
UsageBand	33985	NaN	NaN
saledate	1932	1989-01-17 00:00:00	2011-12-30 00:00:00
fiModelDesc	5039	NaN	NaN
fiBaseModel	19798	NaN	NaN
fiSecondaryDesc	43235	NaN	NaN
fiModelSeries	13202	NaN	NaN
fiModelDescriptor	15875	NaN	NaN
ProductSize	62274	NaN	NaN
fiProductClassDesc	56166	NaN	NaN
state	63944	NaN	NaN
ProductGroup	101167	NaN	NaN
ProductGroupDesc	101167	NaN	NaN
Drive_System	46139	NaN	NaN
Enclosure	173932	NaN	NaN
Forks	178300	NaN	NaN
Pad_Type	70614	NaN	NaN
Ride_Control	77685	NaN	NaN
Stick	48829	NaN	NaN
Transmission	140328	NaN	NaN
Turbocharged	75211	NaN	NaN
Blade_Extension	24692	NaN	NaN
Blade_Width	9615	NaN	NaN
Enclosure_Type	21923	NaN	NaN
Engine_Horsepower	23937	NaN	NaN
Hydraulics	141404	NaN	NaN
Pushblock	19463	NaN	NaN
Ripper	83452	NaN	NaN
Scarifier	12719	NaN	NaN
Tip_Control	16207	NaN	NaN

Tire_Size	46339	NaN	NaN
Coupler	184582	NaN	NaN
Coupler_System	40430	NaN	NaN
Grouser_Tracks	40515	NaN	NaN
Hydraulics_Flow	42784	NaN	NaN
Track_Type	84880	NaN	NaN
Undercarriage_Pad_Width	79651	NaN	NaN
Stick_Length	78820	NaN	NaN
Thumb	83093	NaN	NaN
Pattern_Changer	90255	NaN	NaN
Grouser_Type	84653	NaN	NaN
Backhoe_Mounting	78652	NaN	NaN
Blade_Type	38612	NaN	NaN
Travel_Controls	69923	NaN	NaN
Differential_Type	68073	NaN	NaN
Steering_Controls	68679	NaN	NaN

	mean	std	min	25% \
SalesID	1.91971e+06	909021	1.13925e+06	1.41837e+06
SalePrice	31099.7	23036.9	4750	14500
MachineID	1.2179e+06	440992	0	1.0887e+06
ModelID	6889.7	6221.78	28	3259
datasource	134.666	8.96224	121	132
auctioneerID	6.55604	16.9768	0	1
YearMade	1899.16	291.797	1000	1985
MachineHoursCurrentMeter	3457.96	27590.3	0	0
UsageBand	NaN	NaN	NaN	NaN
saledate	NaN	NaN	NaN	NaN
fiModelDesc	NaN	NaN	NaN	NaN
fiBaseModel	NaN	NaN	NaN	NaN
fiSecondaryDesc	NaN	NaN	NaN	NaN
fiModelSeries	NaN	NaN	NaN	NaN
fiModelDescriptor	NaN	NaN	NaN	NaN
ProductSize	NaN	NaN	NaN	NaN
fiProductClassDesc	NaN	NaN	NaN	NaN
state	NaN	NaN	NaN	NaN
ProductGroup	NaN	NaN	NaN	NaN
ProductGroupDesc	NaN	NaN	NaN	NaN
Drive_System	NaN	NaN	NaN	NaN
Enclosure	NaN	NaN	NaN	NaN
Forks	NaN	NaN	NaN	NaN
Pad_Type	NaN	NaN	NaN	NaN
Ride_Control	NaN	NaN	NaN	NaN
Stick	NaN	NaN	NaN	NaN
Transmission	NaN	NaN	NaN	NaN
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	NaN	NaN	NaN	NaN
Pushblock	NaN	NaN	NaN	NaN
Ripper	NaN	NaN	NaN	NaN
Scarifier	NaN	NaN	NaN	NaN
Tip_Control	NaN	NaN	NaN	NaN
Tire_Size	NaN	NaN	NaN	NaN
Coupler	NaN	NaN	NaN	NaN
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	NaN	NaN	NaN	NaN
Blade_Type	NaN	NaN	NaN	NaN
Travel_Controls	NaN	NaN	NaN	NaN
Differential_Type	NaN	NaN	NaN	NaN
Steering_Controls	NaN	NaN	NaN	NaN

	50%	75%	max
SalesID	1.63942e+06	2.24271e+06	6.33334e+06
SalePrice	24000	40000	142000
MachineID	1.27949e+06	1.46807e+06	2.48633e+06
ModelID	4604	8724	37198
datasource	132	136	172
auctioneerID	2	4	99
YearMade	1995	2000	2013
MachineHoursCurrentMeter	0	3025	2.4833e+06
UsageBand	NaN	NaN	NaN
saledate	NaN	NaN	NaN
fiModelDesc	NaN	NaN	NaN
fiBaseModel	NaN	NaN	NaN
fiSecondaryDesc	NaN	NaN	NaN
fiModelSeries	NaN	NaN	NaN
fiModelDescriptor	NaN	NaN	NaN
ProductSize	NaN	NaN	NaN
fiProductClassDesc	NaN	NaN	NaN
state	NaN	NaN	NaN
ProductGroup	NaN	NaN	NaN
ProductGroupDesc	NaN	NaN	NaN
Drive_System	NaN	NaN	NaN
Enclosure	NaN	NaN	NaN
Forks	NaN	NaN	NaN

Pad_Type	NaN	NaN	NaN
Ride_Control	NaN	NaN	NaN
Stick	NaN	NaN	NaN
Transmission	NaN	NaN	NaN
Turbocharged	NaN	NaN	NaN
Blade_Extension	NaN	NaN	NaN
Blade_Width	NaN	NaN	NaN
Enclosure_Type	NaN	NaN	NaN
Engine_Horsepower	NaN	NaN	NaN
Hydraulics	NaN	NaN	NaN
Pushblock	NaN	NaN	NaN
Ripper	NaN	NaN	NaN
Scarifier	NaN	NaN	NaN
Tip_Control	NaN	NaN	NaN
Tire_Size	NaN	NaN	NaN
Coupler	NaN	NaN	NaN
Coupler_System	NaN	NaN	NaN
Grouser_Tracks	NaN	NaN	NaN
Hydraulics_Flow	NaN	NaN	NaN
Track_Type	NaN	NaN	NaN
Undercarriage_Pad_Width	NaN	NaN	NaN
Stick_Length	NaN	NaN	NaN
Thumb	NaN	NaN	NaN
Pattern_Changer	NaN	NaN	NaN
Grouser_Type	NaN	NaN	NaN
Backhoe_Mounting	NaN	NaN	NaN
Blade_Type	NaN	NaN	NaN
Travel_Controls	NaN	NaN	NaN
Differential_Type	NaN	NaN	NaN
Steering_Controls	NaN	NaN	NaN

It's important to note what metric is being used for a project. Generally, selecting the metric(s) is an important part of the project setup. However, in this case Kaggle tells us what metric to use: RMSLE (root mean squared log error) between the actual and predicted auction prices. Therefore we take the log of the prices, so that RMSE will give us what we need.

```
In [73]: df_raw.SalePrice.head()
```

```
Out[73]: 0    66000
         1    57000
         2    10000
         3    38500
         4    11000
         Name: SalePrice, dtype: int64
```

```
In [74]: # since we know they care about RMSLE our dependent variable
         # should be represented as a log
```

```
# numpy can cast every element as a log
df_raw.SalePrice = np.log(df_raw.SalePrice)
```

```
In [75]: df_raw.SalePrice.head()
```

```
Out[75]: 0    11.097410
         1    10.950807
         2     9.210340
         3    10.558414
         4     9.305651
         Name: SalePrice, dtype: float64
```

1.0.1 Initial processing

```
In [76]: # here we create a model that leverages all our cpu/gpu power hence the -1
m = RandomForestRegressor(n_jobs=-1)
# The following code is supposed to fail due to string values in the input data
# here we call fit, fits, general form is the list of independent variables
# and then the independent variables we want to predict
# pandas.drop() will return everything but the dropped column
# then we just pass that column as the dependent variable
# axis = 1 means remove columns
m.fit(df_raw.drop('SalePrice', axis=1), df_raw.SalePrice)
```

ValueError

Traceback (most recent call last)

```
<ipython-input-76-952edc4fb6f1> in <module>()
      7 # then we just pass that column as the dependent variable
      8 # axis = 1 means remove columns
----> 9 m.fit(df_raw.drop('SalePrice', axis=1), df_raw.SalePrice)

~/anaconda3/envs/fastai/lib/python3.6/site-packages/sklearn/ensemble/forest.py in fit(self, X, y, sample_weight)
    245         """
    246         # Validate or convert input data
--> 247         X = check_array(X, accept_sparse="csc", dtype=DTYPE)
    248         y = check_array(y, accept_sparse='csc', ensure_2d=False, dtype=None)
    249         if sample_weight is not None:

~/anaconda3/envs/fastai/lib/python3.6/site-packages/sklearn/utils/validation.py in check_array(array, dtype, order, copy, force_all_finite)
    431         force_all_finite)
    432     else:
--> 433         array = np.array(array, dtype=dtype, order=order, copy=copy)
    434
    435         if ensure_2d:
```

```
ValueError: could not convert string to float: 'Conventional'
```

Machine Learning models need numbers , notice above the fit command didn't work that's because the column conventional is in string format and could not be converted to a float. ML models convert all numbers to floats, or at least SKLearn and Pythorch do.

This dataset contains a mix of **continuous** and **categorical** variables.

The following method extracts particular date fields from a complete datetime for the purpose of constructing categoricals. You should always consider this feature extraction step when working with date-time. Without expanding your date-time into these additional fields, you can't capture any trend/cyclical behavior as a function of time at any of these granularities.

```
In [77]: # notice how this is of type datetime, we actually declared this earlier
# this is not a number its an object
# time to do our first piece of feature engineering
df_raw.saledate.head()
```

```
Out [77]: 0    2006-11-16
1    2004-03-26
2    2004-02-26
3    2011-05-19
4    2009-07-23
Name: saledate, dtype: datetime64[ns]
```

There is a lot going on in a date

```
In [78]: # Here is something very useful from the fastai library
# for handling dates, notice where its from
add_datepart
```

```
Out [78]: <function fastai.structured.add_datepart(df, fldname, drop=True, time=False)>
```

add_datepart is actually really great, it will go through a declared datetime object and see what kind of date data it contains, then it will break all of them into separate columns of number the model can digest, and finally delete the original datetime object from the dataframe.

```
In [79]: df_raw.columns
```

```
Out [79]: Index(['SalesID', 'SalePrice', 'MachineID', 'ModelID', 'datasource',
'auctioneerID', 'YearMade', 'MachineHoursCurrentMeter', 'UsageBand',
'saledate', 'fiModelDesc', 'fiBaseModel', 'fiSecondaryDesc',
'fiModelSeries', 'fiModelDescriptor', 'ProductSize',
'fiProductClassDesc', 'state', 'ProductGroup', 'ProductGroupDesc',
'Drive_System', 'Enclosure', 'Forks', 'Pad_Type', 'Ride_Control',
'Stick', 'Transmission', 'Turbocharged', 'Blade_Extension',
'Blade_Width', 'Enclosure_Type', 'Engine_Horsepower', 'Hydraulics',
'Pushblock', 'Ripper', 'Scarifier', 'Tip_Control', 'Tire_Size',
```

```

        'Coupler', 'Coupler_System', 'Grouser_Tracks', 'Hydraulics_Flow',
        'Track_Type', 'Undercarriage_Pad_Width', 'Stick_Length', 'Thumb',
        'Pattern_Changer', 'Grouser_Type', 'Backhoe_Mounting', 'Blade_Type',
        'Travel_Controls', 'Differential_Type', 'Steering_Controls'],
        dtype='object')

```

```

In [80]: add_datepart(df_raw, 'saledate')
         df_raw.saleYear.head()

```

```

Out [80]: 0    2006
          1    2004
          2    2004
          3    2011
          4    2009
          Name: saleYear, dtype: int64

```

```

In [81]: # notice sale date is now gone and the parts that were used
         # to make it up now have their own columns
         df_raw.columns

```

```

Out [81]: 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', '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', 'saleYear', 'saleMonth',
                 'saleWeek', 'saleDay', 'saleDayofweek', 'saleDayofyear',
                 'saleIs_month_end', 'saleIs_month_start', 'saleIs_quarter_end',
                 'saleIs_quarter_start', 'saleIs_year_end', 'saleIs_year_start',
                 'saleElapsed'],
                 dtype='object')

```

This solves our datetime object problem but not our string problem, things like 'low', 'high', 'medium'

```

In [82]: df_raw.head()

```

```

Out [82]:   SalesID  SalePrice  MachineID  ModelID  datasource  auctioneerID  YearMade  \
0   1139246   11.097410     999089      3157           121           3.0      2004
1   1139248   10.950807     117657        77           121           3.0      1996
2   1139249    9.210340     434808     7009           121           3.0      2001
3   1139251   10.558414    1026470      332           121           3.0      2001

```



```

4  1139253    9.305651    1057373    17311          121          3.0    2007

    MachineHoursCurrentMeter UsageBand fiModelDesc    ...    saleDay  \
0                68.0        Low        521D    ...        16
1             4640.0        Low       950FII    ...        26
2             2838.0        High        226    ...        26
3             3486.0        High    PC120-6E    ...        19
4              722.0    Medium        S175    ...        23

    saleDayofweek saleDayofyear saleIs_month_end saleIs_month_start  \
0                3          320          False          False
1                4           86          False          False
2                3           57          False          False
3                3          139          False          False
4                3          204          False          False

    saleIs_quarter_end saleIs_quarter_start saleIs_year_end saleIs_year_start  \
0                False          False          False          False
1                False          False          False          False
2                False          False          False          False
3                False          False          False          False
4                False          False          False          False

    saleElapsed
0  1163635200
1  1080259200
2  1077753600
3  1305763200
4  1248307200

[5 rows x 65 columns]

```

The categorical variables are currently stored as strings, which is inefficient, and doesn't provide the numeric coding required for a random forest. Therefore we call `train_cats` to convert strings to pandas categories. Pandas has a built in concept for categories, but by default it doesn't turn anything into a category.

```

In [83]: # train_cats is our solution
         # there is some nuance here however
         # when assigning categories it is important to be consistent
         # notice how this is called "train"_cats
         # this is for the training set
         # when you try and train your model you typically have a train and valid set
         # so 'high' might be 0 in train but it could be 2 in valid
         # for future reference this is why fastai has a apply_cats(df, trn)
         # you can pass the data frame of the validation set as well as the
         # applied categories from the train set to achieve aforementioned consistency
         train_cats(df_raw)

```

We can specify the order to use for categorical variables if we wish:

```
In [84]: # UsageBand used to be a column of strings where as now
# it is a category so we can now call .cat
df_raw.UsageBand.cat.categories
```

```
Out[84]: Index(['High', 'Low', 'Medium'], dtype='object')
```

```
In [85]: # things may work a little better if you first order your categories
df_raw.UsageBand.cat.set_categories(['High', 'Medium', 'Low'], ordered=True, inplace=True)
```

```
In [91]: # notice it is of type categories
# which pandas is totally cool with
#df_raw.UsageBand.head()
os.makedirs('tmp', exist_ok=True)
df_raw.to_feather('tmp/bulldozers-raw')
```

```
In [87]: # here are the category types
df_raw.UsageBand.cat.categories
```

```
Out[87]: Index(['High', 'Medium', 'Low'], dtype='object')
```

```
In [88]: # now lets see the codes instead of the strings
df_raw.UsageBand.cat.codes.head()
```

```
Out[88]: 0    2
         1    2
         2    0
         3    0
         4    1
         dtype: int8
```

We're still not quite done - for instance we have lots of missing values, which we can't pass directly to a random forest.

```
In [89]: # isnull will find how many elements are null
# sum() will add that and give a number back
# then we can sort them and divide by the size of the dataset
# this will show use the percent of null values in a given column
display_all(df_raw.isnull().sum().sort_index()/len(df_raw))
```

Backhoe_Mounting	0.803872
Blade_Extension	0.937129
Blade_Type	0.800977
Blade_Width	0.937129
Coupler	0.466620
Coupler_System	0.891660
Differential_Type	0.826959
Drive_System	0.739829
Enclosure	0.000810

Enclosure_Type	0.937129
Engine_Horsepower	0.937129
Forks	0.521154
Grouser_Tracks	0.891899
Grouser_Type	0.752813
Hydraulics	0.200823
Hydraulics_Flow	0.891899
MachineHoursCurrentMeter	0.644089
MachineID	0.000000
ModelID	0.000000
Pad_Type	0.802720
Pattern_Changer	0.752651
ProductGroup	0.000000
ProductGroupDesc	0.000000
ProductSize	0.525460
Pushblock	0.937129
Ride_Control	0.629527
Ripper	0.740388
SalePrice	0.000000
SalesID	0.000000
Scarifier	0.937102
Steering_Controls	0.827064
Stick	0.802720
Stick_Length	0.752651
Thumb	0.752476
Tip_Control	0.937129
Tire_Size	0.763869
Track_Type	0.752813
Transmission	0.543210
Travel_Controls	0.800975
Turbocharged	0.802720
Undercarriage_Pad_Width	0.751020
UsageBand	0.826391
YearMade	0.000000
auctioneerID	0.050199
datasource	0.000000
fiBaseModel	0.000000
fiModelDesc	0.000000
fiModelDescriptor	0.820707
fiModelSeries	0.858129
fiProductClassDesc	0.000000
fiSecondaryDesc	0.342016
saleDay	0.000000
saleDayofweek	0.000000
saleDayofyear	0.000000
saleElapsed	0.000000
saleIs_month_end	0.000000
saleIs_month_start	0.000000

```

saleIs_quarter_end      0.000000
saleIs_quarter_start    0.000000
saleIs_year_end          0.000000
saleIs_year_start        0.000000
saleMonth                0.000000
saleWeek                 0.000000
saleYear                 0.000000
state                    0.000000
dtype: float64

```

But let's save this file for now, since it's already in format can we be stored and accessed efficiently.

```

In [90]: # This will save our dataframe for further use and transport
         # also the feather format is really good for saving
         # large amounts of data very fast
         # becoming a standard
         #os.makedirs('tmp', exist_ok=True)
         #df_raw.to_feather('tmp/bulldozers-raw')

```

1.0.2 Pre-processing

In the future we can simply read it from this fast format.

```

In [ ]: #df_raw = pd.read_feather('tmp/bulldozers-raw')

```

We'll replace categories with their numeric codes, handle missing continuous values, and split the dependent variable into a separate variable.

```

In [29]: # now we will be using another tool from the fastai library called proc_df
         # this takes in a dataframe object and the dependent variable
         # copy data frame
         # grab y value
         # drop dependent variable from original
         # then it call fix_missing
         proc_df

```

```

Out[29]: <function fastai.structured.proc_df(df, y_fld=None, skip_flds=None, ignore_flds=None,

```

```

In [30]: # this is called in the function above
         # it takes in a df, col, and name
         # it checks that a value is actually missing
         # if its numeric it replaces the missing variables with the median
         # value in the column
         # pandas handles categorical variables automatically by setting them to -1

         # if its not numeric and its a categorical type
         # from wht i understand it bumps everyting up by one
         # so -1 will be 0, 0 will become 1, 1 will become 2 ... and so on
         fix_missing

```

```
Out[30]: <function fastai.structured.fix_missing(df, col, name, na_dict)>
```

```
In [31]: df, y, nas = proc_df(df_raw, 'SalePrice')
```

```
In [32]: # notice now, everything is a number
df.head()
```

```
Out[32]:
```

	SalesID	MachineID	ModelID	datasource	auctioneerID	YearMade	\
0	1139246	999089	3157	121	3.0	2004	
1	1139248	117657	77	121	3.0	1996	
2	1139249	434808	7009	121	3.0	2001	
3	1139251	1026470	332	121	3.0	2001	
4	1139253	1057373	17311	121	3.0	2007	

	MachineHoursCurrentMeter	UsageBand	fiModelDesc	fiBaseModel	\
0	68.0	3	950	296	
1	4640.0	3	1725	527	
2	2838.0	1	331	110	
3	3486.0	1	3674	1375	
4	722.0	2	4208	1529	

	...	saleDayofyear	saleIs_month_end	\
0	...	320	False	
1	...	86	False	
2	...	57	False	
3	...	139	False	
4	...	204	False	

	saleIs_month_start	saleIs_quarter_end	saleIs_quarter_start	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	

	saleIs_year_end	saleIs_year_start	saleElapsed	auctioneerID_na	\
0	False	False	1163635200	False	
1	False	False	1080259200	False	
2	False	False	1077753600	False	
3	False	False	1305763200	False	
4	False	False	1248307200	False	

	MachineHoursCurrentMeter_na
0	False
1	False
2	False
3	False
4	False

[5 rows x 66 columns]

We now have something we can pass to a random forest!

```
In [33]: m = RandomForestRegressor(n_jobs=-1)
         m.fit(df, y)
         m.score(df,y)
```

```
Out[33]: 0.9831480803038706
```

In statistics, the coefficient of determination, denoted R^2 or r^2 and pronounced “R squared”, is the proportion of the variance in the dependent variable that is predictable from the independent variable(s). https://en.wikipedia.org/wiki/Coefficient_of_determination

Wow, an r^2 of 0.98 - that’s great, right? Well, perhaps not...

Possibly **the most important idea** in machine learning is that of having separate training & validation data sets. As motivation, suppose you don’t divide up your data, but instead use all of it. And suppose you have lots of parameters:

Underfitting and Overfitting

The error for the pictured data points is lowest for the model on the far right (the blue curve passes through the red points almost perfectly), yet it’s not the best choice. Why is that? If you were to gather some new data points, they most likely would not be on that curve in the graph on the right, but would be closer to the curve in the middle graph.

This illustrates how using all our data can lead to **overfitting**. A validation set helps diagnose this problem.

```
In [34]: # here is just a quick splitting of the data into a train and test set
         # I'm pretty sure we don't have a validation
         # set because we don't need one
         def split_vals(a,n):
             return a[:n].copy(), a[n:].copy()

         n_valid = 12000 # same as Kaggle's test set size
         n_trn = len(df)-n_valid
         raw_train, raw_valid = split_vals(df_raw, n_trn)
         X_train, X_valid = split_vals(df, n_trn)
         y_train, y_valid = split_vals(y, n_trn)

         X_train.shape, y_train.shape, X_valid.shape, y_valid.shape
```

```
Out[34]: ((389125, 66), (389125,), (12000, 66), (12000,))
```

2 Random Forests

2.1 Base model

Let’s try our model again, this time with separate training and validation sets.

```
In [35]: def rmse(x,y): return math.sqrt(((x-y)**2).mean())

def print_score(m):
    # gives rmse for both train and valid then accuracy (r^2) for each
    res = [rmse(m.predict(X_train), y_train), rmse(m.predict(X_valid), y_valid),
            m.score(X_train, y_train), m.score(X_valid, y_valid)]
    if hasattr(m, 'oob_score_'): res.append(m.oob_score_)
    print(res)

In [36]: m = RandomForestRegressor(n_jobs=-1)
         %time m.fit(X_train, y_train)
         print_score(m)

CPU times: user 1min 18s, sys: 552 ms, total: 1min 18s
Wall time: 16.3 s
[0.09023701101160281, 0.2533649711716698, 0.9829821681203281, 0.8853586960612733]
```

An r^2 in the high-80's isn't bad at all (and the RMSLE puts us around rank 100 of 470 on the Kaggle leaderboard), but we can see from the validation set score that we're over-fitting badly. To understand this issue, let's simplify things down to a single small tree.

2.2 Speeding things up

```
In [37]: # this will randomly sample 30000 rows
         df_trn, y_trn, nas = proc_df(df_raw, 'SalePrice', subset=30000, na_dict=nas)
         # then we will take new values for the training sets x values
         # and y values, the _ is just a generally accepted practice for throwing
         # a variable away
         X_train, _ = split_vals(df_trn, 20000)
         y_train, _ = split_vals(y_trn, 20000)

In [38]: X_train.shape, y_train.shape

Out[38]: ((20000, 66), (20000,))

In [39]: m = RandomForestRegressor(n_jobs=-1)
         %time m.fit(X_train, y_train)
         print_score(m)

CPU times: user 3.41 s, sys: 24 ms, total: 3.43 s
Wall time: 810 ms
[0.11155338743152253, 0.37539404082299194, 0.972510943059477, 0.7483350570726175]
```

2.3 Single tree

```
In [40]: # in sklearn trees are referred to as estimators
         # random trees randomize a buch of things
```

```

# bootstrap = False disables that
# this is a poor model btw
m = RandomForestRegressor(n_estimators=1, max_depth=3, bootstrap=False, n_jobs=-1)
m.fit(X_train, y_train)
print_score(m)

```

```
[0.5205144895789622, 0.5828702179892538, 0.40150577711834023, 0.3932752591762205]
```

```

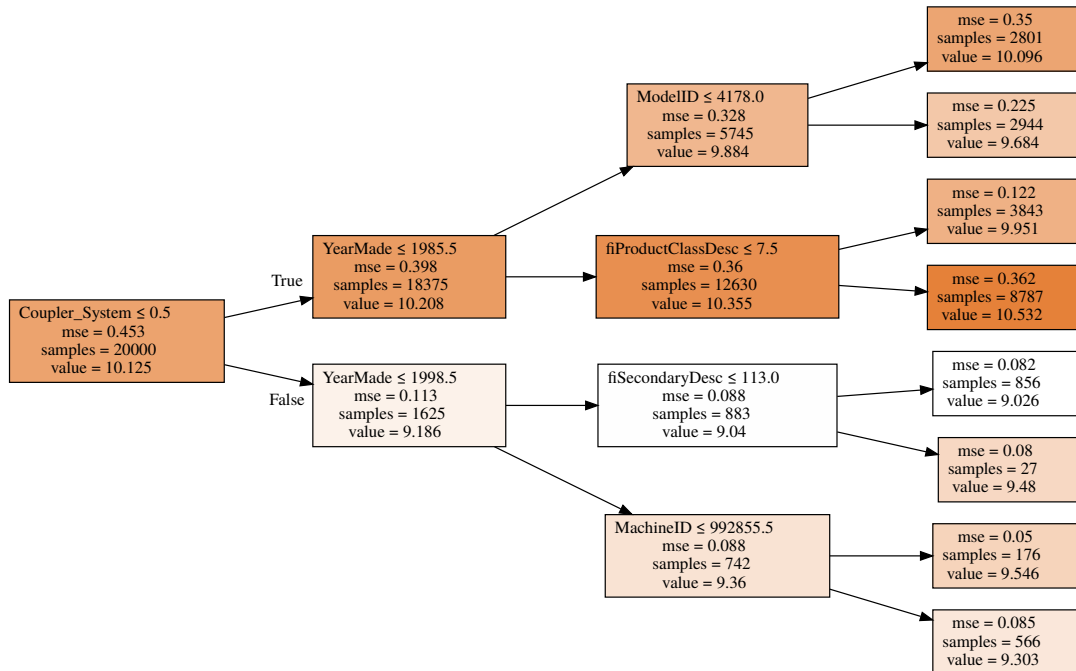
In [41]: # a tree consists of a sequence of binary splits
# notice we start with 20000 rows
# this uses graphiz
# the average of the log is 10.098
# the most basic is a sing leaf which is just predict the average
# we are trying to improve the mse or mean squared error
# so when coupler stems is not less than .5 we improve that
# by alot, however if it is less than the mse doesn't improve much
# we can also see how the samples split False has a lot less
# how should we make our first binary decsion?
# find a variable that we could split in two such that the two grups
# are as different as possible

# test all possible splits
# for each variable for each possible value of
# that varibale see wether its better

# here is the answer:
# take a weighted average
# take 0.4 * 18317 and add it to .111*1638 for instance
# then compared this weighted average to all other possible splits
# that is how we know where best to make the fist split

# you stop at depth variable or when there are not more splits
draw_tree(m.estimators_[0], df_trn, precision=3)

```

In [42]: *# better than shallow tree but not good enough*

```
m = RandomForestRegressor(n_estimators=1, bootstrap=False, n_jobs=-1)
m.fit(X_train, y_train)
print_score(m)
```

[6.993523870246153e-17, 0.46839068491988145, 1.0, 0.6081999627307028]

The training set result looks great! But the validation set is worse than our original model. This is why we need to use *bagging* of multiple trees to get more generalizable results.

2.4 Bagging

2.4.1 Intro to bagging

To learn about bagging in random forests, let's start with our basic model again.

In [43]: *# by default this will create 10 trees*

```
# we're looking for a low RMSE for the validation set
# new hyper parameter: number of trees
m = RandomForestRegressor(n_jobs=-1)
m.fit(X_train, y_train)
print_score(m)
```

[0.11096356235686501, 0.3588938445334113, 0.9728008647077702, 0.7699723760625773]

```
In [44]: # a random forest is just a way to bag trees
# averaging different models is the technique for ensembling
# create big deep massively overfit trees
# but only use say 1/10 of the data
# let's say we do it 100 times
# all res will be better than nothing
# but they overfit terribly
# They all overfit in different ways for different things
# What is the average of a bunch of random errors? ans: 0
# so if we take the average the erros will average out to 0
```

We'll grab the predictions for each individual tree, and look at one example.

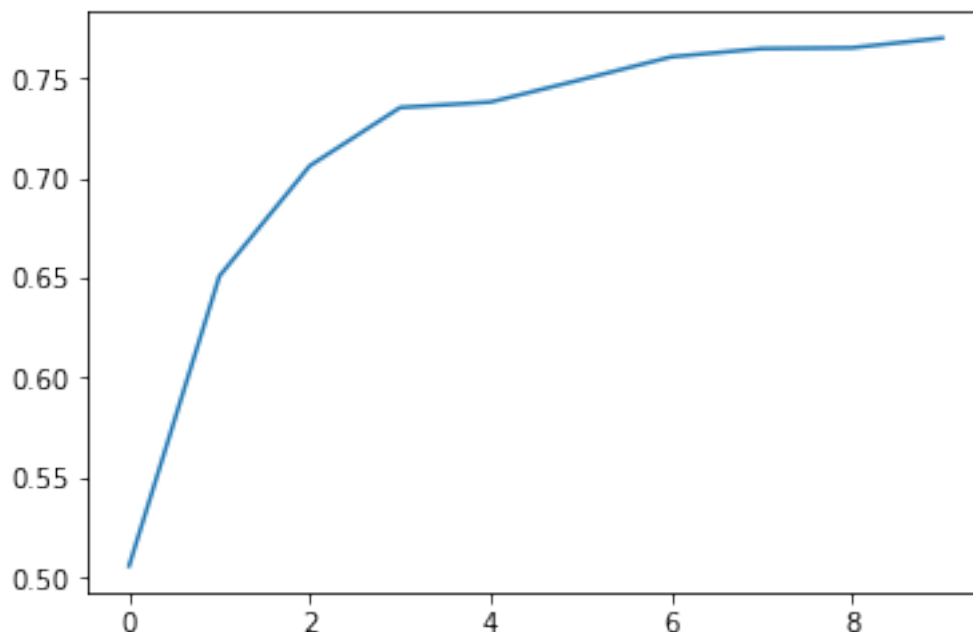
```
In [45]: preds = np.stack([t.predict(X_valid) for t in m.estimators_])
preds[:,0], np.mean(preds[:,0]), y_valid[0]
```

```
Out[45]: (array([9.18502, 9.15905, 9.15905, 9.13238, 9.15905, 9.71112, 9.04782, 9.18502, 9.13238,
9.185807794479167,
9.104979856318357])
```

```
In [46]: preds.shape
```

```
Out[46]: (10, 12000)
```

```
In [47]: plt.plot([metrics.r2_score(y_valid, np.mean(preds[:i+1], axis=0)) for i in range(10)])
```



The shape of this curve suggests that adding more trees isn't going to help us much. Let's check. (Compare this to our original model on a sample)

```
In [48]: #m = RandomForestRegressor(n_estimators=20, n_jobs=-1)
        #m.fit(X_train, y_train)
        #print_score(m)

In [49]: #m = RandomForestRegressor(n_estimators=40, n_jobs=-1)
        #m.fit(X_train, y_train)
        #print_score(m)

In [50]: #m = RandomForestRegressor(n_estimators=80, n_jobs=-1)
        #m.fit(X_train, y_train)
        #print_score(m)
```

2.4.2 Out-of-bag (OOB) score

Is our validation set worse than our training set because we're over-fitting, or because the validation set is for a different time period, or a bit of both? With the existing information we've shown, we can't tell. However, random forests have a very clever trick called *out-of-bag (OOB) error* which can handle this (and more!)

The idea is to calculate error on the training set, but only include the trees in the calculation of a row's error where that row was *not* included in training that tree. This allows us to see whether the model is over-fitting, without needing a separate validation set.

This also has the benefit of allowing us to see whether our model generalizes, even if we only have a small amount of data so want to avoid separating some out to create a validation set.

This is as simple as adding one more parameter to our model constructor. We print the OOB error last in our `print_score` function below.

```
In [53]: ## OOB score is at the end of this list
        # notice how the  $r^2$  is similar to the validation set (although not as close as jeremy's)
        m = RandomForestRegressor(n_estimators=200, n_jobs=-1, oob_score=True)
        m.fit(X_train, y_train)
        print_score(m)

[0.0912914003222948, 0.34298413795784344, 0.981589988778005, 0.789914516164208, 0.866072294377
```

This shows that our validation set time difference is making an impact, as is model over-fitting.

2.5 Reducing over-fitting

2.5.1 Subsampling

It turns out that one of the easiest ways to avoid over-fitting is also one of the best ways to speed up analysis: *subsampling*. Let's return to using our full dataset, so that we can demonstrate the impact of this technique.

```
In [54]: df_trn, y_trn, nas = proc_df(df_raw, 'SalePrice')
        X_train, X_valid = split_vals(df_trn, n_trn)
        y_train, y_valid = split_vals(y_trn, n_trn)

In [55]: len(df_raw)
```

```
Out [55]: 401125
```

```
In [56]: len(X_train)
```

```
Out [56]: 389125
```

The basic idea is this: rather than limit the total amount of data that our model can access, let's instead limit it to a *different* random subset per tree. That way, given enough trees, the model can still see *all* the data, but for each individual tree it'll be just as fast as if we had cut down our dataset as before.

```
In [57]: # now we can just grab a set of 20000
         set_rf_samples(20000)
```

```
In [58]: m = RandomForestRegressor(n_jobs=-1, oob_score=True)
         %time m.fit(X_train, y_train)
         print_score(m)
```

```
CPU times: user 21.4 s, sys: 1.73 s, total: 23.1 s
```

```
Wall time: 5.5 s
```

```
[0.2406191876413026, 0.2779289143235192, 0.878997222690765, 0.8620519912663209, 0.866416202213...
```

Since each additional tree allows the model to see more data, this approach can make additional trees more useful.

```
In [59]: m = RandomForestRegressor(n_estimators=40, n_jobs=-1, oob_score=True)
         m.fit(X_train, y_train)
         print_score(m)
```

```
[0.22756925726761643, 0.26527282472021885, 0.8917664233471054, 0.8743294551866888, 0.880152434...
```

2.5.2 Tree building parameters

We revert to using a full bootstrap sample in order to show the impact of other over-fitting avoidance methods.

```
In [60]: reset_rf_samples()
```

Let's get a baseline for this full set to compare to.

```
In [61]: m = RandomForestRegressor(n_estimators=40, n_jobs=-1, oob_score=True)
         m.fit(X_train, y_train)
         print_score(m)
```

```
[0.07826057371819195, 0.236993210786384, 0.9871996784119512, 0.8996956463677973, 0.90853561181...
```

Another way to reduce over-fitting is to grow our trees less deeply. We do this by specifying (with `min_samples_leaf`) that we require some minimum number of rows in every leaf node. This has two benefits: