Bulldozer Blue Book - using RandomForest

March 4, 2019

0.0.1 Blue Book for Bulldozer - Kaggle Competition

This notebook is mostly created using the steps explained in the excellent Machine Learning course by Jeremy Howard and developed by Jeremy Howard and Rachel Thomas. The courses are available at http://www.fast.ai/

The idea behind this notebook is to take the reader step by step of how to use RandomForest in any competition. I have tried to clarify some aspects for a beginner and give reasons for some decision taken.

The high levels steps are as follows 1. Create the best model possible using only the training set (Train.csv) - Pre-process the training dataset and change all categories to codes, impute missing values and add some variables. - Split the dataset into training and validation sets (validation set being nearly the same size as the Kaggle provided validation set. - Separate the dependent variable. - Create the base model using all variables. - From the base model, find out the most important features and remove all unimportant features from the dataset. - Run the model again using only important features. - Detect and remove redundant features - Remove features which have a temporal sequence to make the model more general 2. Train the model on the whole training set - Run randomforest with a large number of entimators and finetuned paramters on the whole Kaggle provided training dataset. - This is the final model. 3. Apply the model on validation set (Valid.csv) and predict the SalePrice - Combine the Kaggle provided training and validation sets and pre-process the data. - Separate the datasets into training and validation and fit the above created model using the training data. - Predict the dependent variable using this fitted model. 4. Calculate the RMSLE using the actual SalePrice in the training set and the predicted SalePrice.

Notes: 1. I could not import the 'fastai' package into a Windows 10 environment and hence have included the 'fastai' functions I used in the notebook. 2. To run the notebook, the path to the dataset needs to be provided. 3. Further optimization of the model is possible by using the Machine_Appendix.csv which contains a more accurate year of manufacture and some more attributes. 4. Jeremy Howard also suggested using one-hot encoding of some variables. This has not been included here. 5. The course by Jeremy stops at finding the RMSE score using a validation set derived from the training set. I have used the actual validation set provided by Kaggle to calculate the final RMSE. This is what Kaggle would do if you submit your productions.

Environment Setup Import necessary packages

```
In [84]: import pandas as pd
         import re
         from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
```

```
from IPython.display import display
import numpy as np
import math
from sklearn import metrics
from pandas.api.types import is_string_dtype, is_numeric_dtype
import matplotlib.pyplot as plt
from sklearn.ensemble import forest
import scipy
from scipy.cluster import hierarchy as hc
```

Compile necessary fastai functions

In [85]:
```
def rmse(x,y):
    return math.sqrt(((x-y)**2).mean())

def print_score(m):
    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)

def split_vals(a,n):
    return a[:n].copy(), a[n:].copy()

def get_oob(df):
    m = RandomForestRegressor(n_estimators=40, min_samples_leaf=5, max_features=0.6, r
    x, _ = split_vals(df, n_trn)
    m.fit(x, y_train)
    return m.oob_score_

def add_datepart(df, fldname, drop=True, time=False):
    fld = df[fldname]
    fld_dtype = fld.dtype
    if isinstance(fld_dtype, pd.core.dtypes.dtypes.DatetimeTZDtype):
        fld_dtype = np.datetime64

    if not np.issubdtype(fld_dtype, np.datetime64):
        df[fldname] = fld = pd.to_datetime(fld, infer_datetime_format=True)
    targ_pre = re.sub('[Dd]ate$', '', fldname)
    attr = ['Year', 'Month', 'Week', 'Day', 'Dayofweek', 'Dayofyear',
            'Is_month_end', 'Is_month_start', 'Is_quarter_end', 'Is_quarter_start', 'I
    if time: attr = attr + ['Hour', 'Minute', 'Second']
    for n in attr: df[targ_pre + n] = getattr(fld.dt, n.lower())
    df[targ_pre + 'Elapsed'] = fld.astype(np.int64) // 10 ** 9
    if drop: df.drop(fldname, axis=1, inplace=True)

def train_cats(df):
    for n,c in df.items():
```

```
            if is_string_dtype(c): df[n] = c.astype('category').cat.as_ordered()

    def fix_missing(df, col, name, na_dict):
        if is_numeric_dtype(col):
            if pd.isnull(col).sum() or (name in na_dict):
                df[name+'_na'] = pd.isnull(col)
                filler = na_dict[name] if name in na_dict else col.median()
                df[name] = col.fillna(filler)
                na_dict[name] = filler
        return na_dict

    def proc_df(df, y_fld=None, skip_flds=None, ignore_flds=None, do_scale=False, na_dict=
                preproc_fn=None, max_n_cat=None, subset=None, mapper=None):
        if not ignore_flds: ignore_flds=[]
        if not skip_flds: skip_flds=[]
        if subset: df = get_sample(df,subset)
        else: df = df.copy()
        ignored_flds = df.loc[:, ignore_flds]
        df.drop(ignore_flds, axis=1, inplace=True)
        if preproc_fn: preproc_fn(df)
        if y_fld is None: y = None
        else:
            if not is_numeric_dtype(df[y_fld]): df[y_fld] = df[y_fld].cat.codes
            y = df[y_fld].values
            skip_flds += [y_fld]
        df.drop(skip_flds, axis=1, inplace=True)

        if na_dict is None: na_dict = {}
        else: na_dict = na_dict.copy()
        na_dict_initial = na_dict.copy()
        for n,c in df.items(): na_dict = fix_missing(df, c, n, na_dict)
        if len(na_dict_initial.keys()) > 0:
            df.drop([a + '_na' for a in list(set(na_dict.keys()) - set(na_dict_initial.ke
        if do_scale: mapper = scale_vars(df, mapper)
        for n,c in df.items(): numericalize(df, c, n, max_n_cat)
        df = pd.get_dummies(df, dummy_na=True)
        df = pd.concat([ignored_flds, df], axis=1)
        res = [df, y, na_dict]
        if do_scale: res = res + [mapper]
        return res

    def numericalize(df, col, name, max_n_cat):
        if not is_numeric_dtype(col) and ( max_n_cat is None or col.nunique()>max_n_cat):
            df[name] = col.cat.codes+1
```

Dataset import and pre-processing

```
In [86]: df_raw = pd.read_csv('Train.csv', low_memory=False, parse_dates=['saledate'])
```

In [87]: df_raw.head()

```
Out[87]:    SalesID  SalePrice  MachineID  ModelID  datasource  auctioneerID  YearMade  \
         0  1139246      66000     999089     3157         121           3.0      2004
         1  1139248      57000     117657       77         121           3.0      1996
         2  1139249      10000     434808     7009         121           3.0      2001
         3  1139251      38500    1026470      332         121           3.0      2001
         4  1139253      11000    1057373    17311         121           3.0      2007

            MachineHoursCurrentMeter UsageBand   saledate        ...         \
         0                      68.0       Low 2006-11-16        ...
         1                    4640.0       Low 2004-03-26        ...
         2                    2838.0      High 2004-02-26        ...
         3                    3486.0      High 2011-05-19        ...
         4                     722.0    Medium 2009-07-23        ...

           Undercarriage_Pad_Width Stick_Length Thumb Pattern_Changer Grouser_Type  \
         0                     NaN          NaN   NaN             NaN          NaN
         1                     NaN          NaN   NaN             NaN          NaN
         2                     NaN          NaN   NaN             NaN          NaN
         3                     NaN          NaN   NaN             NaN          NaN
         4                     NaN          NaN   NaN             NaN          NaN

           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

           Steering_Controls
         0      Conventional
         1      Conventional
         2               NaN
         3               NaN
         4               NaN

         [5 rows x 53 columns]
```

In [88]:
```
#Change SalePrice to log because the evaluation is for RMSLE
df_raw.SalePrice = np.log(df_raw.SalePrice)
#Change dates to date parts
add_datepart(df_raw, 'saledate')
#Add a column for age of bulldozer
df_raw['age'] = df_raw['saleYear'] - df_raw['YearMade']
```

In [89]:
```
#Change string variables to category type
train_cats(df_raw)
```

```python
#Specify order for variable UsageBand and change to codes
df_raw.UsageBand.cat.set_categories(['High', 'Medium', 'Low'], ordered=True, inplace=
df_raw.UsageBand = df_raw.UsageBand.cat.codes
#Change categories to code and missing values to 0, replace missing numeric values wi
#add column to indicate replaced missing values and separate the dependent variable a
df, y, nas = proc_df(df_raw, 'SalePrice')
```

In [90]:
```python
df.head()
```

Out[90]:
```
   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          2          950          296
1                    4640.0          2         1725          527
2                    2838.0          0          331          110
3                    3486.0          0         3674         1375
4                     722.0          1         4208         1529

              ...                saleIs_month_end  saleIs_month_start  \
0             ...                           False               False
1             ...                           False               False
2             ...                           False               False
3             ...                           False               False
4             ...                           False               False

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

   saleIs_year_start  saleElapsed  age  auctioneerID_na  \
0              False   1163635200    2            False
1              False   1080259200    8            False
2              False   1077753600    3            False
3              False   1305763200   10            False
4              False   1248307200    2            False

   MachineHoursCurrentMeter_na
0                        False
1                        False
2                        False
```

```
3                         False
4                         False

[5 rows x 67 columns]
```

In [91]:
```
df.shape
```

Out[91]:
```
(401125, 67)
```

Run the base model

In [92]:
```
#Split the dataset into training and validation sets. Use 12,000 as the validation se

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) #for using unprocessed data if neede
X_train, X_valid = split_vals(df, n_trn)
y_train, y_valid = split_vals(y, n_trn)
```

In [93]:
```
X_train.shape, X_valid.shape, y_train.shape, y_valid.shape
```

Out[93]:
```
((389125, 67), (12000, 67), (389125,), (12000,))
```

In [94]:
```
#Run base model
m = RandomForestRegressor(n_jobs=-1)
m.fit(X_train, y_train)
print_score(m);
```

```
C:\Users\sureshsu\AppData\Local\Continuum\anaconda\lib\site-packages\sklearn\ensemble\forest.py
  warn("Some inputs do not have OOB scores. "


[0.0908084299709318, 0.24578352609030657, 0.9827659574789724, 0.8921168757587268, -1.301829396
```

This model is pretty good and we are already in the top 25% of the leaderboard!

Feature Engineering Various methods are used to remove unimportant and redundant features. This not only simplifies the model but also improves the scores.

Feature importance

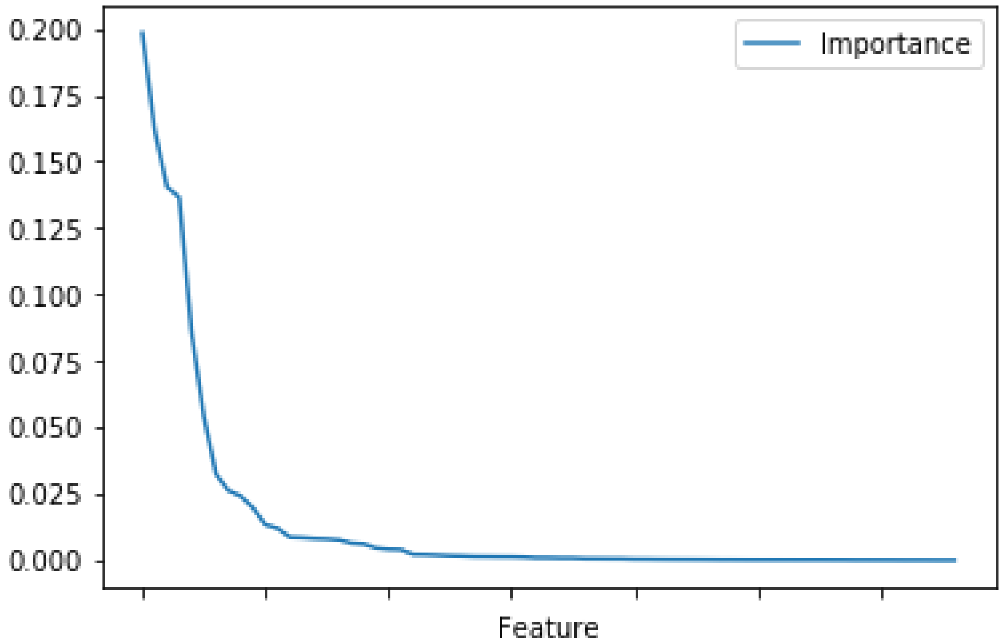
In [95]:
```
#Use the feature importance to find the most important ones
feature_importance = pd.DataFrame({'Feature' : X_train.columns, 'Importance' : m.featu
feature_importance.sort_values('Importance', ascending=False, inplace=True)
feature_importance.head(30)
```

Out[95]:

	Feature	Importance
37	Coupler_System	0.198409
64	age	0.162049
14	fiProductClassDesc	0.140629
13	ProductSize	0.136602
2	ModelID	0.086065
5	YearMade	0.054311
10	fiSecondaryDesc	0.032405
63	saleElapsed	0.026305
8	fiModelDesc	0.024194
0	SalesID	0.019793
9	fiBaseModel	0.013425
1	MachineID	0.012067
18	Drive_System	0.008716
19	Enclosure	0.008542
15	state	0.008207
56	saleDayofyear	0.008050
54	saleDay	0.007693
12	fiModelDescriptor	0.006474
11	fiModelSeries	0.006144
4	auctioneerID	0.004638
53	saleWeek	0.004165
55	saleDayofweek	0.004031
51	saleYear	0.002224
6	MachineHoursCurrentMeter	0.002146
41	Undercarriage_Pad_Width	0.001947
52	saleMonth	0.001734
35	Tire_Size	0.001621
32	Ripper	0.001424
36	Coupler	0.001398
48	Travel_Controls	0.001341

```
In [96]: feature_importance.plot('Feature', 'Importance')
```

```
Out[96]: <matplotlib.axes._subplots.AxesSubplot at 0x16b82e86668>
```



In [97]:
```
# Run the model for various cut off values for the importance to find the best set of
for i in [0.001, 0.002, 0.003, 0.004, 0.005, 0.006, 0.007, 0.008, 0.009, 0.010, 0.011
    important_features = feature_importance[feature_importance['Importance'] > i]
    df_important = df[important_features['Feature']]
    X_train, X_valid = split_vals(df_important, n_trn)
    y_train, y_valid = split_vals(y, n_trn)

    m = RandomForestRegressor(n_estimators=40, min_samples_leaf=3, max_features=0.5, r
    m.fit(X_train, y_train)
    print_score(m)
```

```
[0.11958432619003426, 0.22574406793833476, 0.9701129295238532, 0.9089917700653886, 0.911072227
[0.12049563941770408, 0.22521344572791402, 0.9696556745688437, 0.909419105617885, 0.910660572
[0.12147071811939218, 0.22505634357621612, 0.9691625808353372, 0.9095454345765783, 0.909983230
[0.12163997253531515, 0.22516687691586804, 0.969076584708487, 0.909456561716612, 0.90980214663
[0.12506905819081568, 0.22492477218285567, 0.9673085197916903, 0.9096511659165414, 0.909343905
[0.12492540750136373, 0.22312856564640468, 0.9673835736348412, 0.9110884213642689, 0.909598157
[0.12557639305226187, 0.22526850212388036, 0.9670427599482362, 0.9093748128169125, 0.908587497
[0.12703377677814198, 0.22586670449312324, 0.9662733468549793, 0.9088928618859209, 0.908646855
[0.13982977644922445, 0.22748791683229216, 0.9591366325656094, 0.9075802814655586, 0.902676425
[0.1397763420435576, 0.22785794064870832, 0.9591678575679768, 0.9072793836450362, 0.9028576744
[0.13990402619920667, 0.22836470188417285, 0.9590932240664158, 0.9068664995096065, 0.902723695
[0.1397628228046279, 0.2291276198573204, 0.9591757557971861, 0.9062431815650996, 0.90282509611
```

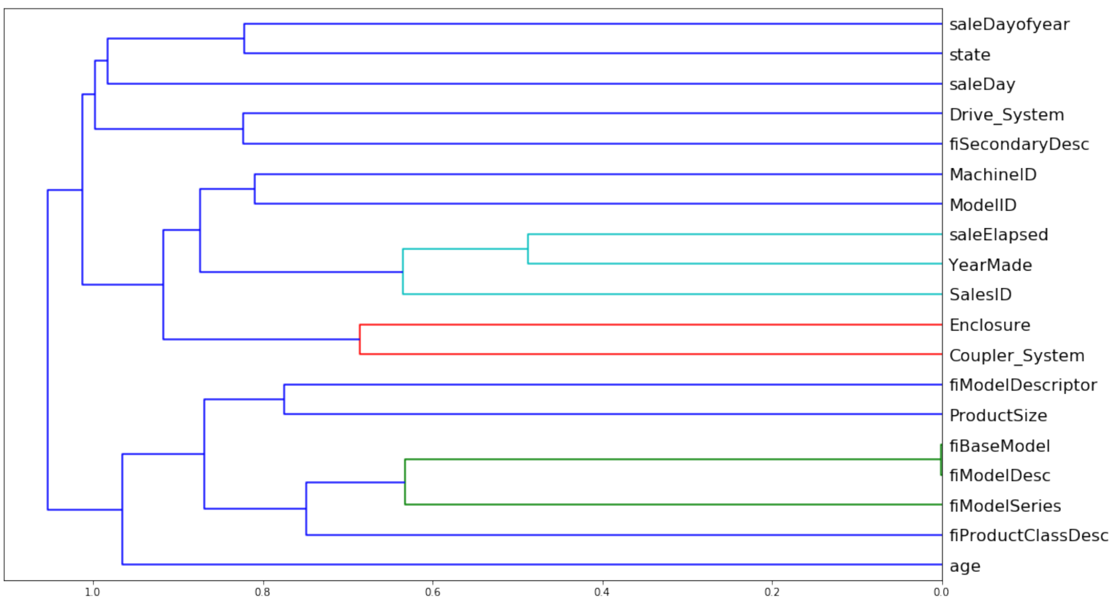
In [102]:
```
#The best cut off point seems to be 0.0.006 when the RMSE score is 0.22312856564640
important_features = feature_importance[feature_importance['Importance'] > 0.006]
```

```
df_important = df[important_features['Feature']]
X_train, X_valid = split_vals(df_important, n_trn)
y_train, y_valid = split_vals(y, n_trn)

m = RandomForestRegressor(n_estimators=40, min_samples_leaf=3, max_features=0.5, n_jo
m.fit(X_train, y_train)
print_score(m)
```

```
[0.1250724684536177, 0.22574589686847144, 0.9673067369676975, 0.9089902954010024, 0.90926260504
```

```
In [103]: #Detect and remove redundant features
          #Draw dendogram of feature clusters
          corr = np.round(scipy.stats.spearmanr(df_important).correlation, 4)
          corr_condensed = hc.distance.squareform(1-corr)
          z = hc.linkage(corr_condensed, method='average')
          fig = plt.figure(figsize=(16,10))
          dendrogram = hc.dendrogram(z, labels=df_important.columns, orientation='left', leaf_
          plt.show()
```




```
In [104]: #These feature pairs are in the same cluster'
          cluster_pairs = ['saleDayofyear', 'state', 'Drive_System', 'fiSecondaryDesc', 'Machin
          #Base OOB score
          get_oob(df_important)

Out[104]: 0.9080690969512725

In [106]: #Get the OOB score after dropping each of the variables in the cluster pairs
          for c in cluster_pairs:
              print(c, get_oob(df_important.drop(c, axis=1)))
```

```
saleDayofyear 0.906652296995623
state 0.9069376388210585
Drive_System 0.9069918364443399
fiSecondaryDesc 0.9058226111808125
MachineID 0.9090263081411097
ModelID 0.9073620274524163
saleElapsed 0.9021302468853822
YearMade 0.9075222798267965
Enclosure 0.9071869846567197
Coupler_System 0.9076748150212717
fiModelDescriptor 0.907722618507296
ProductSize 0.9048964672254667
fiBaseModel 0.9072082779412237
fiModelDesc 0.9073429977917062
```

In [108]:
```
#For each pair select the attribute which impacts the score less (score is higher) a
to_drop = ['state', 'Drive_System', 'MachineID', 'Coupler_System', 'fiModelDescripto
get_oob(df_important.drop(to_drop, axis=1))
```

Out[108]: 0.9051640773213453

In [109]:
```
#OOB score has decreased slightly after removing attributes but model has become sim
#Run the random forest on the dataset after dropping the columns
df_keep = df_important.drop(to_drop, axis=1)
X_train, X_valid = split_vals(df_keep, n_trn)
m = RandomForestRegressor(n_estimators=40, min_samples_leaf=3, max_features=0.5, n_j
m.fit(X_train, y_train)
print_score(m)
```

```
[0.1345880561373964, 0.2307505977006369, 0.9621428542287741, 0.9049102636524801, 0.90639876771
```

In [110]:
```
df_keep.columns
```

Out[110]:
```
Index(['age', 'fiProductClassDesc', 'ProductSize', 'ModelID', 'YearMade',
       'fiSecondaryDesc', 'saleElapsed', 'SalesID', 'fiBaseModel', 'Enclosure',
       'saleDayofyear', 'saleDay', 'fiModelSeries'],
      dtype='object')
```

In [111]:
```
#Remove time related features to generalize the model more
#Label the validation and training set and calculate the OOB score
df_ext = df_keep.copy()
df_ext['is_valid'] = 1
df_ext.is_valid[:n_trn] = 0
x, y, nas = proc_df(df_ext, 'is_valid')

m = RandomForestClassifier(n_estimators=40, min_samples_leaf=3, max_features=0.5, n_
m.fit(x, y);
m.oob_score_
```

```
C:\Users\sureshsu\AppData\Local\Continuum\anaconda\lib\site-packages\ipykernel_launcher.py:5: S
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """
```

Out[111]: 0.9999975070115301

In [112]:
```
#Very high OOB score
#Find the important features, i.e. the features which help rf predict the validation
feature_importance_ext = pd.DataFrame({'Feature' : x.columns, 'Importance' : m.featu
feature_importance_ext.sort_values('Importance', ascending=False, inplace=True)
feature_importance_ext.head(30)
```

Out[112]:

	Feature	Importance
7	SalesID	0.818795
6	saleElapsed	0.165247
4	YearMade	0.004877
10	saleDayofyear	0.004170
3	ModelID	0.001886
0	age	0.001536
8	fiBaseModel	0.001210
9	Enclosure	0.001184
11	saleDay	0.000442
1	fiProductClassDesc	0.000225
5	fiSecondaryDesc	0.000194
12	fiModelSeries	0.000149
2	ProductSize	0.000088

In [113]:
```
#Drop the top 1 and see if the RMSe improves
to_drop = ['SalesID']
df_keep = df_important.drop(to_drop, axis=1)
X_train, X_valid = split_vals(df_keep, n_trn)
m = RandomForestRegressor(n_estimators=40, min_samples_leaf=3, max_features=0.5, n_jo
m.fit(X_train, y_train)
print_score(m)
```

```
[0.1275097246760018, 0.2218735477023768, 0.9660201511974527, 0.9120857998199207, 0.90923642789
```

There is a slight improvement.

In [114]:
```
#Run the final model
m = RandomForestRegressor(n_estimators=160, max_features=0.5, n_jobs=-1, oob_score=Tr
m.fit(X_train, y_train)
print_score(m)
```

```
[0.07445680529666567, 0.21570860916579637, 0.9884137306018732, 0.9169034618469332, 0.915210280
```

The final model looks pretty good and the RMSE decreased from to 0.21570860916579637, mainly due to feature selection and fine tuning parameters.

What we have essentially done in the previous steps is to fine tune the hyper parameters and select the subset of features which gives the best score and generalizes the model the best. So the best model is RandomForestRegressor(n_estimators=160, max_features=0.5, n_jobs=-1, oob_score=True) and the features to use are df_keep.columns

Run model on actual validaiton set Now lets train the model on the full training dataset and check the score on the validation set provided by Kaggle.

To get the same set of category codes and uniformly imputing missing values, we are joining the training and validation sets and pre-processing them together. After preprocessing we will separate them again

```
In [115]: #Import data
          df_raw = pd.read_csv('Train.csv', low_memory=False, parse_dates=['saledate'])
          df_validation = pd.read_csv('Valid.csv', low_memory=False, parse_dates=['saledate'])
```

Just to be sure, check the column names and columns in the Training and validation sets.

```
In [116]: print('training shape',df_raw.shape)
          print('validation shape', df_validation.shape)
          print('difference between training and validaiton', set(df_raw.columns) - set(df_vali

training shape (401125, 53)
validation shape (11573, 52)
difference between training and validaiton {'SalePrice'}
```

```
In [117]: #Separate out the SalePrice as y and change it to log and drop it from the training
          y = np.log(df_raw['SalePrice'])
          df_raw = df_raw.drop('SalePrice', axis=1)

In [118]: #Append the validation set to the training set
          df_train_valid = df_raw.append(df_validation)

In [119]: df_train_valid.shape

Out[119]: (412698, 52)

In [120]: #Change dates to date parts
          add_datepart(df_train_valid, 'saledate')

In [121]: #Add a column for age of bulldozer
          df_train_valid['age'] = df_train_valid['saleYear'] - df_train_valid['YearMade']

In [122]: #Change string variables to category type
          train_cats(df_train_valid)

In [123]: #Specify order for variable UsageBand and change to codes
          df_train_valid.UsageBand.cat.set_categories(['High', 'Medium', 'Low'], ordered=True,
          df_train_valid.UsageBand = df_train_valid.UsageBand.cat.codes
```

```
In [124]: #Change other categories into codes and replace NaNs with 0.
          cat_cols = list(df_train_valid.select_dtypes(include=['category']).columns)  #Above c
          for col in cat_cols:
              s = df_train_valid[col]
              df_train_valid[col] = s.cat.codes+1

In [125]: #Replace the NaNs for the numerical column with mean
          df_train_valid['auctioneerID'].fillna(df_train_valid['auctioneerID'].median(), inplac
          df_train_valid['MachineHoursCurrentMeter'].fillna(df_train_valid['MachineHoursCurrent

In [126]: #Check if df has NaNs
          df_train_valid.isnull().sum()

Out[126]: SalesID                     0
          MachineID                   0
          ModelID                     0
          datasource                  0
          auctioneerID                0
          YearMade                    0
          MachineHoursCurrentMeter    0
          UsageBand                   0
          fiModelDesc                 0
          fiBaseModel                 0
          fiSecondaryDesc             0
          fiModelSeries               0
          fiModelDescriptor           0
          ProductSize                 0
          fiProductClassDesc          0
          state                       0
          ProductGroup                0
          ProductGroupDesc            0
          Drive_System                0
          Enclosure                   0
          Forks                       0
          Pad_Type                    0
          Ride_Control                0
          Stick                       0
          Transmission                0
          Turbocharged                0
          Blade_Extension             0
          Blade_Width                 0
          Enclosure_Type              0
          Engine_Horsepower           0
                                     ..
          Tire_Size                   0
          Coupler                     0
          Coupler_System              0
          Grouser_Tracks              0
```

```
Hydraulics_Flow            0
Track_Type                 0
Undercarriage_Pad_Width    0
Stick_Length               0
Thumb                      0
Pattern_Changer            0
Grouser_Type               0
Backhoe_Mounting           0
Blade_Type                 0
Travel_Controls            0
Differential_Type          0
Steering_Controls          0
saleYear                   0
saleMonth                  0
saleWeek                   0
saleDay                    0
saleDayofweek              0
saleDayofyear              0
saleIs_month_end           0
saleIs_month_start         0
saleIs_quarter_end         0
saleIs_quarter_start       0
saleIs_year_end            0
saleIs_year_start          0
saleElapsed                0
age                        0
Length: 65, dtype: int64
```

In [127]:
```
df_train_valid.head()
```

Out[127]:
```
   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          2          963          298 ...
1                    4640.0          2         1745          529 ...
2                    2838.0          0          336          111 ...
3                    3486.0          0         3716         1381 ...
4                     722.0          1         4261         1538 ...

   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  \
0               False                 False            False
1               False                 False            False
2               False                 False            False
3               False                 False            False
4               False                 False            False

   saleIs_year_start  saleElapsed  age
0              False   1163635200    2
1              False   1080259200    8
2              False   1077753600    3
3              False   1305763200   10
4              False   1248307200    2

[5 rows x 65 columns]
```

In [128]:
```
df_train_valid.shape
```

Out[128]:
```
(412698, 65)
```

The pre-processed dataset is ready. Now need to choose only columns which were in our final model and run the model.

In [129]:
```
# These were the columns in the final model
df_keep.columns
```

Out[129]:
```
Index(['Coupler_System', 'age', 'fiProductClassDesc', 'ProductSize', 'ModelID',
       'YearMade', 'fiSecondaryDesc', 'saleElapsed', 'fiModelDesc',
       'fiBaseModel', 'MachineID', 'Drive_System', 'Enclosure', 'state',
       'saleDayofyear', 'saleDay', 'fiModelDescriptor', 'fiModelSeries'],
      dtype='object')
```

In [130]:
```
#Choose only columns which were used in the final model
df_train_valid = df_train_valid[df_keep.columns]

#Separate the training and validation sets
df_valid = df_train_valid.tail(11573)
df_train = df_train_valid.head(401125)
```

In [131]:
```
print(df_valid.shape)
print(df_train.shape)
```

```
(11573, 18)
(401125, 18)
```

In [132]:
```
#Train the model on training set and dependent variable using out final model
m = RandomForestRegressor(n_estimators=160, max_features=0.5, n_jobs=-1, oob_score=T
m.fit(df_train, y)
```

Out[132]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features=0.5, max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=160, n_jobs=-1,
           oob_score=True, random_state=None, verbose=0, warm_start=False)
```

In [133]:
```
#Import the validation solution
solution = pd.read_csv('ValidSolution.csv', low_memory=False)
y_actual = np.log(solution.SalePrice)
```

In [134]:
```
#Calculate the RMSE using the prediction from the validation set and the actual prov
rmse(m.predict(df_valid), y_actual)
```

Out[134]:
```
0.24618093599623628
```

That's it! Further fine tuning can be done by selecting a differnt combinations of features and perhaps replacing YearMade with the corrected data. I leave to the reader to do these and better the score above.
Hope this notebook helped!