

sale_prediction_of_bulldozer

November 12, 2019

```
[ ]: # Bulldozer sale prediction is a regression task and for predicting the model ,  
    ↪ algorithm used is RandomForest  
    # The dependent variable is Sale Price and independent variable is rest all  
    ↪ attributes like machineID, Saledate etc.  
    # The evaluation metric used here is RMSLE (Root mean square Log Error). In this  
    ↪ We first take the mean of squared  
    # differences of log values. We take a square root of the result obtained.  
    # This is equivalent to calculating the root mean squared error (rmse) of log  
    ↪ of the values.  
    # The R2 is a statistical measure of how close the data are to the fittest line
```

```
[63]: %load_ext autoreload  
      %autoreload 2  
      %matplotlib inline
```

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

```
%reload_ext autoreload
```

```
[2]: from fastai.imports import *  
     from fastai.tabular import *  
     from pandas_summary import DataFrameSummary  
     from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier  
     from IPython.display import display  
     from sklearn import metrics  
     import numpy as np  
     from pandas.api.types import is_string_dtype, is_numeric_dtype,  
     ↪ is_categorical_dtype  
     from sklearn.preprocessing import LabelEncoder, Imputer, StandardScaler
```

```
[4]: # Reading the CSV data file(Train file)
```

```
[5]: data_read=pd.read_csv('Train.csv', low_memory=False, parse_dates=["saledate"])
```

```
[66]: data_read.head()
```

```
[66]:   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	...	Undercarriage_Pad_Width	\
0	68.0	Low	2006-11-16	...		NaN
1	4640.0	Low	2004-03-26	...		NaN
2	2838.0	High	2004-02-26	...		NaN
3	3486.0	High	2011-05-19	...		NaN
4	722.0	Medium	2009-07-23	...		NaN

	Stick_Length	Thumb	Pattern_Changer	Grouser_Type	Backhoe_Mounting	Blade_Type	\
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN

	Travel_Controls	Differential_Type	Steering_Controls
0	NaN	Standard	Conventional
1	NaN	Standard	Conventional
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	NaN	NaN

[5 rows x 53 columns]

```
[6]: def display_alldata(df):
      with pd.option_context('display.max_rows', 1000, 'display.max_columns', 1000):
          display(df)
```

```
[69]: display_alldata(data_read.head().transpose())
```

	0	\
SalesID	1139246	
SalePrice	66000	
MachineID	999089	
ModelID	3157	
datasource	121	
auctioneerID	3	
YearMade	2004	
MachineHoursCurrentMeter	68	
UsageBand	Low	
saledate	2006-11-16 00:00:00	
fiModelDesc	521D	
fiBaseModel	521	

fiSecondaryDesc	D
fiModelSeries	NaN
fiModelDescriptor	NaN
ProductSize	NaN
fiProductClassDesc	Wheel Loader - 110.0 to 120.0 Horsepower
state	Alabama
ProductGroup	WL
ProductGroupDesc	Wheel Loader
Drive_System	NaN
Enclosure	EROPS w AC
Forks	None or Unspecified
Pad_Type	NaN
Ride_Control	None or Unspecified
Stick	NaN
Transmission	NaN
Turbocharged	NaN
Blade_Extension	NaN
Blade_Width	NaN
Enclosure_Type	NaN
Engine_Horsepower	NaN
Hydraulics	2 Valve
Pushblock	NaN
Ripper	NaN
Scarifier	NaN
Tip_Control	NaN
Tire_Size	None or Unspecified
Coupler	None or Unspecified
Coupler_System	NaN
Grouser_Tracks	NaN
Hydraulics_Flow	NaN
Track_Type	NaN
Undercarriage_Pad_Width	NaN
Stick_Length	NaN
Thumb	NaN
Pattern_Changer	NaN
Grouser_Type	NaN
Backhoe_Mounting	NaN
Blade_Type	NaN
Travel_Controls	NaN
Differential_Type	Standard
Steering_Controls	Conventional
1 \	
SalesID	1139248
SalePrice	57000
MachineID	117657
ModelID	77
datasource	121

auctioneerID	3
YearMade	1996
MachineHoursCurrentMeter	4640
UsageBand	Low
saledate	2004-03-26 00:00:00
fiModelDesc	950FII
fiBaseModel	950
fiSecondaryDesc	F
fiModelSeries	II
fiModelDescriptor	NaN
ProductSize	Medium
fiProductClassDesc	Wheel Loader - 150.0 to 175.0 Horsepower
state	North Carolina
ProductGroup	WL
ProductGroupDesc	Wheel Loader
Drive_System	NaN
Enclosure	EROPS w AC
Forks	None or Unspecified
Pad_Type	NaN
Ride_Control	None or Unspecified
Stick	NaN
Transmission	NaN
Turbocharged	NaN
Blade_Extension	NaN
Blade_Width	NaN
Enclosure_Type	NaN
Engine_Horsepower	NaN
Hydraulics	2 Valve
Pushblock	NaN
Ripper	NaN
Scarifier	NaN
Tip_Control	NaN
Tire_Size	23.5
Coupler	None or Unspecified
Coupler_System	NaN
Grouser_Tracks	NaN
Hydraulics_Flow	NaN
Track_Type	NaN
Undercarriage_Pad_Width	NaN
Stick_Length	NaN
Thumb	NaN
Pattern_Changer	NaN
Grouser_Type	NaN
Backhoe_Mounting	NaN
Blade_Type	NaN
Travel_Controls	NaN
Differential_Type	Standard
Steering_Controls	Conventional

		2 \
SalesID		1139249
SalePrice		10000
MachineID		434808
ModelID		7009
datasource		121
auctioneerID		3
YearMade		2001
MachineHoursCurrentMeter		2838
UsageBand		High
saledate		2004-02-26 00:00:00
fiModelDesc		226
fiBaseModel		226
fiSecondaryDesc		NaN
fiModelSeries		NaN
fiModelDescriptor		NaN
ProductSize		NaN
fiProductClassDesc	Skid Steer Loader - 1351.0 to 1601.0 Lb Operat...	
state		New York
ProductGroup		SSL
ProductGroupDesc		Skid Steer Loaders
Drive_System		NaN
Enclosure		OROPS
Forks		None or Unspecified
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		None or Unspecified
Grouser_Tracks		None or Unspecified
Hydraulics_Flow		Standard
Track_Type		NaN
Undercarriage_Pad_Width		NaN
Stick_Length		NaN
Thumb		NaN

Pattern_Changer	NaN
Grouser_Type	NaN
Backhoe_Mounting	NaN
Blade_Type	NaN
Travel_Controls	NaN
Differential_Type	NaN
Steering_Controls	NaN

	3 \
SalesID	1139251
SalePrice	38500
MachineID	1026470
ModelID	332
datasource	121
auctioneerID	3
YearMade	2001
MachineHoursCurrentMeter	3486
UsageBand	High
saledate	2011-05-19 00:00:00
fiModelDesc	PC120-6E
fiBaseModel	PC120
fiSecondaryDesc	NaN
fiModelSeries	-6E
fiModelDescriptor	NaN
ProductSize	Small
fiProductClassDesc	Hydraulic Excavator, Track - 12.0 to 14.0 Metr...
state	Texas
ProductGroup	TEX
ProductGroupDesc	Track Excavators
Drive_System	NaN
Enclosure	EROPS w AC
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	2 Valve
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	NaN
Undercarriage_Pad_Width	NaN
Stick_Length	NaN
Thumb	NaN
Pattern_Changer	NaN
Grouser_Type	NaN
Backhoe_Mounting	NaN
Blade_Type	NaN
Travel_Controls	NaN
Differential_Type	NaN
Steering_Controls	NaN

	4
SalesID	1139253
SalePrice	11000
MachineID	1057373
ModelID	17311
datasource	121
auctioneerID	3
YearMade	2007
MachineHoursCurrentMeter	722
UsageBand	Medium
saledate	2009-07-23 00:00:00
fiModelDesc	S175
fiBaseModel	S175
fiSecondaryDesc	NaN
fiModelSeries	NaN
fiModelDescriptor	NaN
ProductSize	NaN
fiProductClassDesc	Skid Steer Loader - 1601.0 to 1751.0 Lb Operat...
state	New York
ProductGroup	SSL
ProductGroupDesc	Skid Steer Loaders
Drive_System	NaN
Enclosure	EROPS
Forks	None or Unspecified
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	None or Unspecified
Grouser_Tracks	None or Unspecified
Hydraulics_Flow	Standard
Track_Type	NaN
Undercarriage_Pad_Width	NaN
Stick_Length	NaN
Thumb	NaN
Pattern_Changer	NaN
Grouser_Type	NaN
Backhoe_Mounting	NaN
Blade_Type	NaN
Travel_Controls	NaN
Differential_Type	NaN
Steering_Controls	NaN

```
[ ]: # Data Preprocessing as we can see so many categorical values in data frame
      ↪ like sale data Usage band .Its necessary to
      # convert categorical value to numerical value to feed into tree.
```

```
[34]: datavalue=np.log(data_read.SalePrice)
```

```
[37]: print(datavalue)
```

```
0      11.097410
1      10.950807
2       9.210340
3      10.558414
4       9.305651
...
401120    9.259131
401121    9.305651
401122    9.350102
401123    9.104980
401124    8.955448
Name: SalePrice, Length: 401125, dtype: float64
```

```
[70]: def add_datepart(df, fldname, drop=True):
      fld = df[fldname]
      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)
for n in ('Year', 'Month', 'Week', 'Day', 'Dayofweek',
          'Dayofyear', 'Is_month_end', 'Is_month_start',
          'Is_quarter_end', 'Is_quarter_start', 'Is_year_end',
          'Is_year_start'):
    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)

```

```

[71]: fld = data_read.saledate
      fld.dt.year

```

```

[71]: 0      2006
      1      2004
      2      2004
      3      2011
      4      2009
      ...
      401120  2011
      401121  2011
      401122  2011
      401123  2011
      401124  2011
      Name: saledate, Length: 401125, dtype: int64

```

```

[72]: add_datepart(data_read, 'saledate')

```

```

[74]: data_read.saleYear.head()

```

```

[74]: 0      2006
      1      2004
      2      2004
      3      2011
      4      2009
      Name: saleYear, dtype: int64

```

```

[77]: def train_cats(df):
      for n,c in df.items():
          if is_string_dtype(c): df[n] = c.astype('category').cat.as_ordered()

```

```

[83]: train_cats(data_read)

```

```

[85]: data_read.UsageBand.cat.set_categories(['High', 'Medium', 'Low'],
      ordered=True, inplace=True)

```

```
[ ]: # The below code is used to find the null values in dataframe as we can see so many null values(NAN)
```

```
[86]: display_all(data_read.isnull().sum().sort_index()/len(data_read))
```

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

```
[89]: os.makedirs('featherformat', exist_ok=True)
      data_read.to_feather('tmp/featherfile')
```

```
[90]: data_read = pd.read_feather('tmp/featherfile')
```

```
[ ]: # The below functions viz fix_missing, numericalize , cat_to_numeric three_
      ↪function is used to remove null values and to
      # convert categorical values to numerical value
```

```
[7]: 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
```

```
[8]: def numericalize(df, col, name, max_n_cat):
      if not is_numeric_dtype(col) and ( max_n_cat is None or len(col.cat.
      ↪categories)>max_n_cat):
```

```
df[name] = pd.Categorical(col).codes+1
```

```
[9]: def cat_to_numeric(df, y_fld=None, skip_flds=None, ignore_flds=None,
    ↪do_scale=False, na_dict=None,
        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] = pd.
    ↪Categorical(df[y_fld]).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.keys()))], axis=1, inplace=True)
    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
```

```
[12]: df, y, nas = cat_to_numeric(data_read, 'SalePrice')
```

```
[11]: df.head().transpose()
```

```
[11]:
```

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

UsageBand	2	2	1	1	3
saledate	2647	2148	2131	3753	3281
fiModelDesc	950	1725	331	3674	4208
fiBaseModel	296	527	110	1375	1529
fiSecondaryDesc	41	55	0	0	0
fiModelSeries	0	98	0	45	0
fiModelDescriptor	0	0	0	0	0
ProductSize	0	4	0	6	0
fiProductClassDesc	59	62	39	8	40
state	1	33	32	44	32
ProductGroup	6	6	3	4	3
ProductGroupDesc	6	6	3	4	3
Drive_System	0	0	0	0	0
Enclosure	3	3	6	3	1
Forks	1	1	1	0	1
Pad_Type	0	0	0	0	0
Ride_Control	2	2	0	0	0
Stick	0	0	0	0	0
Transmission	0	0	0	0	0
Turbocharged	0	0	0	0	0
Blade_Extension	0	0	0	0	0
Blade_Width	0	0	0	0	0
Enclosure_Type	0	0	0	0	0
Engine_Horsepower	0	0	0	0	0
Hydraulics	1	1	4	1	4
Pushblock	0	0	0	0	0
Ripper	0	0	0	0	0
Scarifier	0	0	0	0	0
Tip_Control	0	0	0	0	0
Tire_Size	17	12	0	0	0
Coupler	3	3	3	3	3
Coupler_System	0	0	1	0	1
Grouser_Tracks	0	0	1	0	1
Hydraulics_Flow	0	0	3	0	3
Track_Type	0	0	0	0	0
Undercarriage_Pad_Width	0	0	0	0	0
Stick_Length	0	0	0	0	0
Thumb	0	0	0	0	0
Pattern_Changer	0	0	0	0	0
Grouser_Type	0	0	0	0	0
Backhoe_Mounting	0	0	0	0	0
Blade_Type	0	0	0	0	0
Travel_Controls	0	0	0	0	0
Differential_Type	4	4	0	0	0
Steering_Controls	2	2	0	0	0
auctioneerID_na	False	False	False	False	False
MachineHoursCurrentMeter_na	False	False	False	False	False

```
[ ]: # Now we will train the model using dataset in which dependent variable is
      ↳SalePrice and rest all are independent variable. Here as this is a
      # regression task so we use random forest regressor
```

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

/home/abdul/anaconda3/envs/fastai/lib/python3.6/site-packages/sklearn/ensemble/forest.py:245: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.

"10 in version 0.20 to 100 in 0.22.", FutureWarning)

```
[13]: 0.982506543468755
```

```
[ ]: # We have split the dataset into train and valid in which training data shape
      ↳as 389125-rows and 54-columns and valid data
      # set contents 12000-rows and 54 columns
```

```
[16]: def split_vals(a,n):
      return a[:n].copy(), a[n:].copy()
      n_valid = 12000
      n_trn = len(df)-n_valid
      raw_train, raw_valid = split_vals(data_read, 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
```

```
[16]: ((389125, 54), (389125,), (12000, 54))
```

```
[22]: 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)
      m=RandomForestRegressor(n_jobs=-1)
      %time m.fit(X_train, y_train)
      print_score(m)
```

/home/abdul/anaconda3/envs/fastai/lib/python3.6/site-packages/sklearn/ensemble/forest.py:245: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.

"10 in version 0.20 to 100 in 0.22.", FutureWarning)

CPU times: user 1min 13s, sys: 274 ms, total: 1min 13s

Wall time: 23.3 s

```
[3053.999092533897, 8615.798772796306, 0.9823652537442809, 0.8737567902681392]
```

```
[ ]: # From above result we can say that -  
# the training rmse is 0.3053 and validation rmse is 0.86. The r(square) value  
→for training is 0.98 and r(saquare) for  
# valiadtion is 0.87.
```

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

```
[25]: (array([ 9000., 10000.,  9000., 10000.,  9000.,  9000., 16000.,  9000., 10000.,  
10000.]),  
10100.0,  
9000)
```

```
[24]: preds.shape
```

```
[24]: (10, 12000)
```

```
[26]: # Each tree is stored in an attribute called estimators_  
# For each tree, we will predict with our validation set.  
# np.stack concatenates them together on a new axis,  
# so the resulting preds has the shape of (10, 12000) (10 trees, 12000  
→validation set).  
# The mean of 10 predictions for the first data is 10, and the actual value is  
→9.
```

```
[ ]: # now lets tune the hyperparameter and see the result. Here the hyperparameter  
→is estimators.
```

```
[27]: m=RandomForestRegressor(n_estimators=20,n_jobs=-1)  
%time m.fit(X_train, y_train)  
print_score(m)
```

CPU times: user 2min 36s, sys: 695 ms, total: 2min 36s

Wall time: 43.6 s

```
[2775.4709165699182, 8241.811514463157, 0.9854351918180747, 0.8844786408164632]
```

```
[28]: m=RandomForestRegressor(n_estimators=40,n_jobs=-1)  
%time m.fit(X_train, y_train)  
print_score(m)
```

CPU times: user 5min 10s, sys: 927 ms, total: 5min 11s

Wall time: 1min 21s

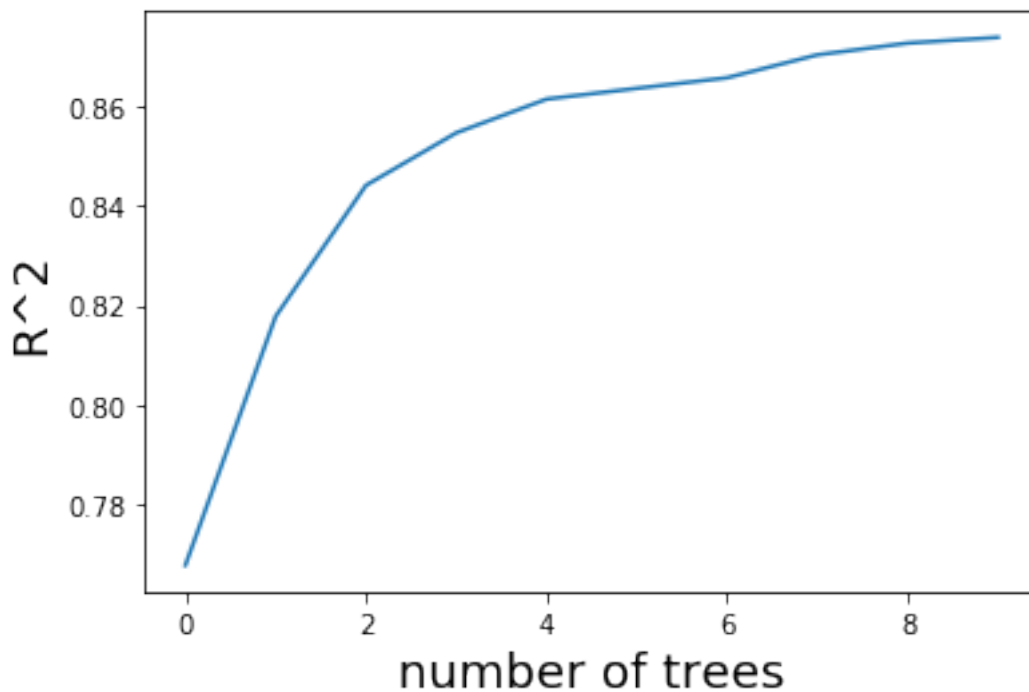
```
[2632.942989539121, 8130.479245490734, 0.9868926674324792, 0.8875785390919012]
```

```
[ ]: # Increasing the number of trees or estimators doesn't make much difference in  
    ↳ the predicted value and actual value.  
    # Adding more trees slows it down, but with less trees you can still draw some  
    ↳ conclusion.
```

```
[ ]: # plot of  $R^2$  vs Numer of trees . As we increase the number of trees the curve  
    ↳ becomes almost flat
```

```
[30]: plt.plot([metrics.r2_score(y_valid, np.mean(preds[:i+1], axis=0)) for i in  
    ↳ range(10)]);  
plt.xlabel('number of trees', fontsize=18)  
plt.ylabel('R^2', fontsize=18)
```

```
[30]: Text(0, 0.5, 'R^2')
```



```
[ ]:
```