Interpreting_your_Data

September 30, 2018

1 Random Forest Model interpretation

```
In [1]: %load_ext autoreload
        %autoreload 2
```

```
In [47]: %matplotlib inline

         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 [48]: set_plot_sizes(12,14,16)
```

1.1 Load in our data

```
In [49]: # point path to data
         PATH = "data/bulldozers/"
```

```
In [50]: # 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 [51]: df_raw.SalePrice = np.log(df_raw.SalePrice)
         add_datepart(df_raw, 'saledate')
         df_raw.saleYear.head()
```

```
Out[51]: 0    2006
         1    2004
         2    2004
         3    2011
         4    2009
         Name: saleYear, dtype: int64
```

In [52]:
```
# 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 aforemention consistency
train_cats(df_raw)
#apply_cats(df_raw)
```

In [53]:
```
df_trn, y_trn, nas = proc_df(df_raw, 'SalePrice')
```

In [54]:
```
def split_vals(a,n): return a[:n], a[n:]
n_valid = 12000
n_trn = len(df_trn)-n_valid
X_train, X_valid = split_vals(df_trn, n_trn)
y_train, y_valid = split_vals(y_trn, n_trn)
raw_train, raw_valid = split_vals(df_raw, n_trn)
```

In [55]:
```
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)
```

In [56]:
```
df_raw.head()
```

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

2 Confidence based on tree variance

For model interpretation, there's no need to use the full dataset on each tree - using a subset will be both faster, and also provide better interpretability (since an overfit model will not provide much variance across trees).

```
In [57]: set_rf_samples(50000)

In [58]: # the validation set is a little worse due to being all from the future
         m = RandomForestRegressor(n_estimators=40, min_samples_leaf=3, max_features=0.5, n_jol
         m.fit(X_train, y_train)
         print_score(m)
```

```
[0.20649529124100546, 0.24944018378023106, 0.910884113505606, 0.8888829227135021, 0.893740027
```

We saw how the model averages predictions across the trees to get an estimate - but how can we know the confidence of the estimate? One simple way is to use the standard deviation of predictions, instead of just the mean. This tells us the *relative* confidence of predictions - that is, for rows where the trees give very different results, you would want to be more cautious of using those results, compared to cases where they are more consistent. Using the same example as in the last lesson when we looked at bagging:

```
In [59]: %time preds = np.stack([t.predict(X_valid) for t in m.estimators_])
         np.mean(preds[:,0]), np.std(preds[:,0])
```

```
CPU times: user 1.38 s, sys: 40 ms, total: 1.42 s
Wall time: 1.43 s
```

Out[59]: (9.250535703082043, 0.2822839234241768)

When we use python to loop through trees like this, we're calculating each in series, which is slow! We can use parallel processing to speed things up:

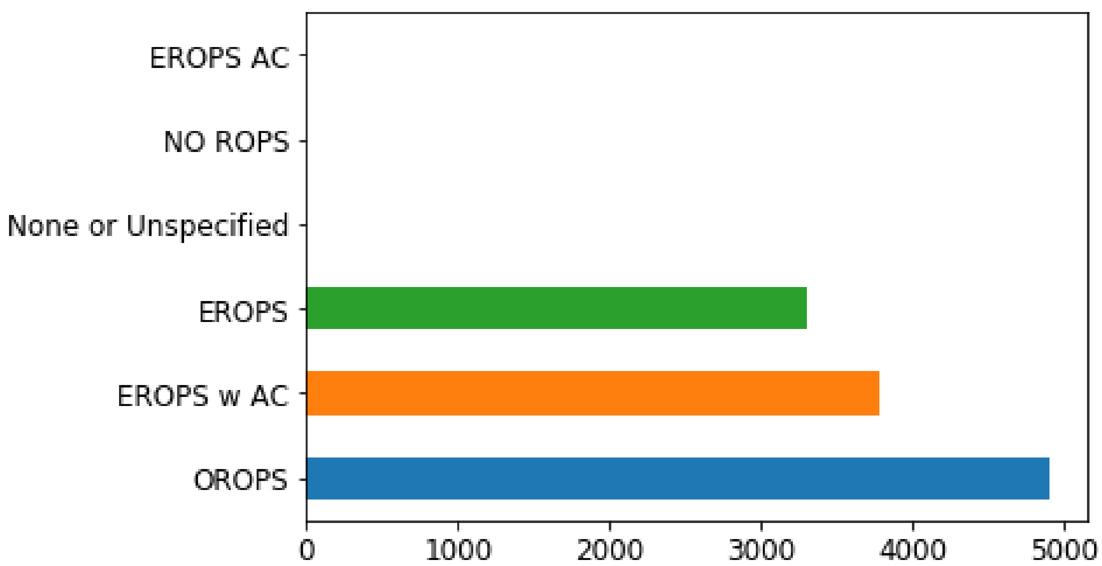
```
In [60]: def get_preds(t): return t.predict(X_valid)
         %time preds = np.stack(parallel_trees(m, get_preds))
         np.mean(preds[:,0]), np.std(preds[:,0])
```

```
CPU times: user 88 ms, sys: 156 ms, total: 244 ms
Wall time: 511 ms
```

Out[60]: (9.250535703082043, 0.2822839234241768)

We can see that different trees are giving different estimates this this auction. In order to see how prediction confidence varies, we can add this into our dataset.

```
In [61]: x = raw_valid.copy()
         x['pred_std'] = np.std(preds, axis=0)
         x['pred'] = np.mean(preds, axis=0)
         x.Enclosure.value_counts().plot.barh();
```

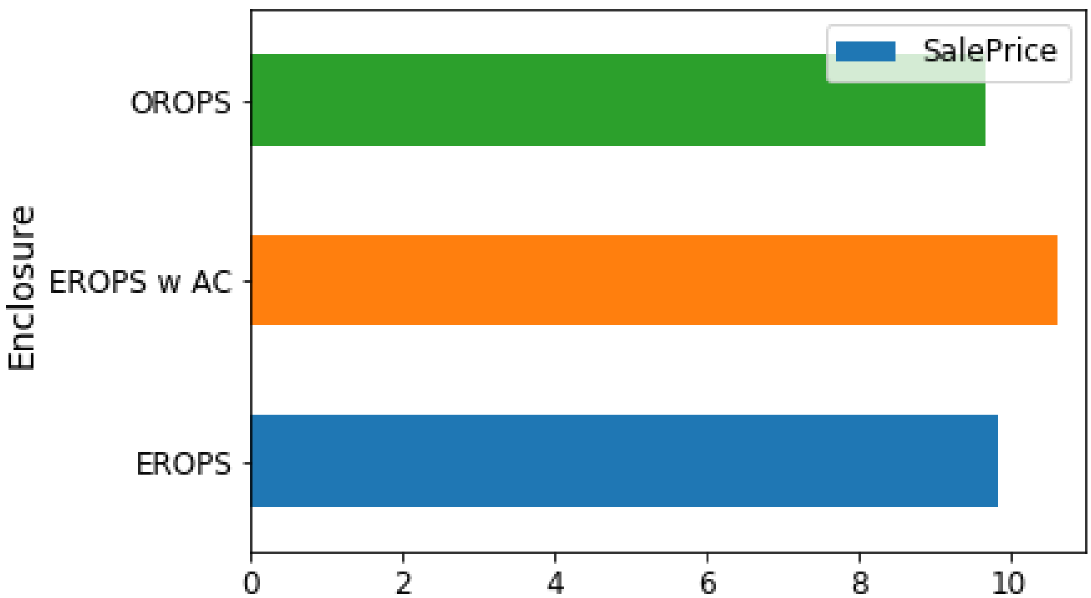



```
In [62]: flds = ['Enclosure', 'SalePrice', 'pred', 'pred_std']
         enc_summ = x[flds].groupby('Enclosure', as_index=False).mean()
         enc_summ
```

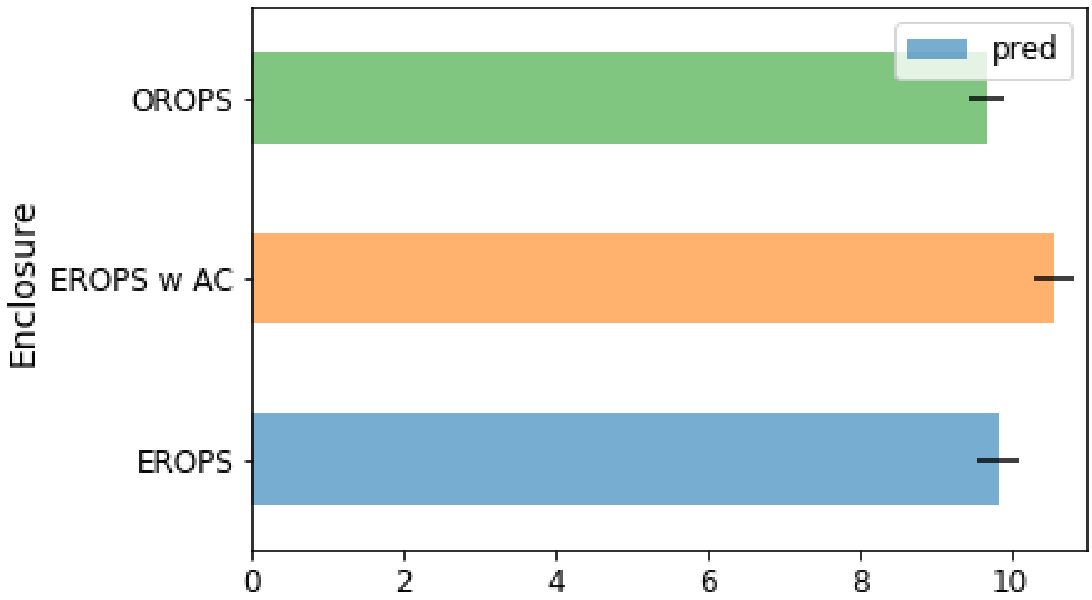
Out[62]:

	Enclosure	SalePrice	pred	pred_std
0	EROPS	9.849178	9.840480	0.278144
1	EROPS AC	NaN	NaN	NaN
2	EROPS w AC	10.623971	10.575259	0.274543
3	NO ROPS	NaN	NaN	NaN
4	None or Unspecified	NaN	NaN	NaN
5	OROPS	9.682064	9.684958	0.218898

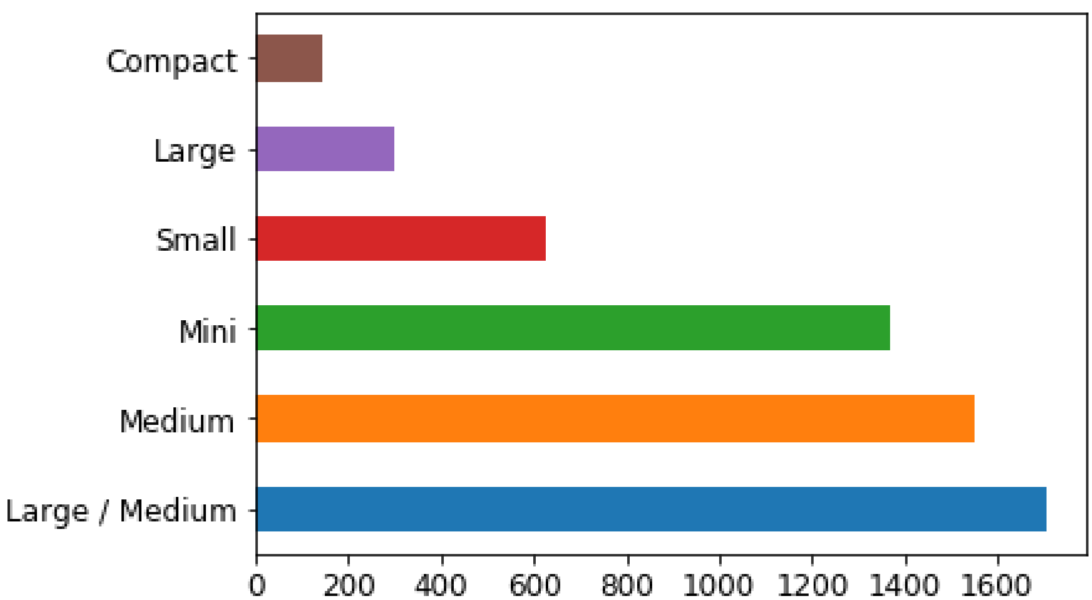
In [63]:
```
enc_summ = enc_summ[~pd.isnull(enc_summ.SalePrice)]
enc_summ.plot('Enclosure', 'SalePrice', 'barh', xlim=(0,11));
```



In [64]:
```
enc_summ.plot('Enclosure', 'pred', 'barh', xerr='pred_std', alpha=0.6, xlim=(0,11));
```




```
In [65]: raw_valid.ProductSize.value_counts().plot.barh();
```




```
In [66]: flds = ['ProductSize', 'SalePrice', 'pred', 'pred_std']
         summ = x[flds].groupby(flds[0]).mean()
         summ
```

Out[66]:
```
              SalePrice       pred  pred_std
ProductSize
Compact        9.735093   9.858105  0.344963
Large         10.470589  10.386889  0.351798
Large / Medium 10.691871 10.646844  0.308542
Medium        10.681511  10.614658  0.289467
Mini           9.535147   9.567300  0.252591
Small         10.324448  10.324686  0.313421
```

In [67]:
```
(summ.pred_std/summ.pred).sort_values(ascending=False)
```

Out[67]:
```
ProductSize
Compact           0.034993
Large             0.033869
Small             0.030356
Large / Medium    0.028980
Medium            0.027270
Mini              0.026401
dtype: float64
```