APA-L8-python

September 6, 2018

1 APA Laboratori 8 - Random Forests

```
In [1]: # Uncomment to upgrade packages
        # !pip install pandas --upgrade
        # !pip install numpy --upgrade
        # !pip install scipy --upgrade
        # !pip install statsmodels --upgrade
        # !pip install scikit-learn --upgrade
        #!pip install imblearn --upgrade
        %load_ext autoreload
```

```
In [2]: import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sn
        import pandas as pd
        from IPython.core.interactiveshell import InteractiveShell
        pd.set_option('precision', 3)
        InteractiveShell.ast_node_interactivity = "all"
```

```
In [3]: # Extra imports
        from pandas import read_csv
        from sklearn.preprocessing import LabelEncoder
        from sklearn.model_selection import train_test_split
        from sklearn.tree import DecisionTreeClassifier
        import graphviz
        from sklearn.tree import export_graphviz
        from sklearn.metrics import confusion_matrix,\
                accuracy_score, classification_report, f1_score
        from sklearn.ensemble import RandomForestClassifier
        from imblearn.under_sampling import RandomUnderSampler
```

```
/home/bejar/.local/lib/python3.6/site-packages/sklearn/ensemble/weight_boosting.py:29: Deprecati
  from numpy.core.umath_tests import inner1d
```

```
In [4]: def confusion(true, pred, classes):
            """
```

```
    Function for pretty printing confusion matrices
    """
    cm =pd.DataFrame(confusion_matrix(true, pred), index=classes,
                 columns=classes)
    cm.index.name = 'Actual'
    cm.columns.name = 'Predicted'
    return cm
```

In [5]:
```
np.random.seed(6046)
```

1.1 Financial Example: classification model for deposit subscription

Direct marketing campaigns (phone calls) of a Portuguese banking institution. The classification goal is to predict if the client will subscribe a term deposit

In [6]:
```
deposit = read_csv("bank-full.csv.gz", header=0, delimiter=';')
deposit.shape
```

Out[6]:
```
(45211, 17)
```

In [7]:
```
deposit.describe(include='all')
```

Out[7]:
```
              age          job  marital  education default      balance  \
count   45211.000        45211    45211      45211   45211    45211.000
unique        NaN           12        3          4       2          NaN
top           NaN  blue-collar  married  secondary      no          NaN
freq          NaN         9732    27214      23202   44396          NaN
mean       40.936          NaN      NaN        NaN     NaN     1362.272
std        10.619          NaN      NaN        NaN     NaN     3044.766
min        18.000          NaN      NaN        NaN     NaN    -8019.000
25%        33.000          NaN      NaN        NaN     NaN       72.000
50%        39.000          NaN      NaN        NaN     NaN      448.000
75%        48.000          NaN      NaN        NaN     NaN     1428.000
max        95.000          NaN      NaN        NaN     NaN   102127.000

       housing   loan   contact        day  month   duration   campaign  \
count    45211  45211     45211  45211.000  45211  45211.000  45211.000
unique       2      2         3        NaN     12        NaN        NaN
top        yes     no  cellular        NaN    may        NaN        NaN
freq     25130  37967     29285        NaN  13766        NaN        NaN
mean       NaN    NaN       NaN     15.806    NaN    258.163      2.764
std        NaN    NaN       NaN      8.322    NaN    257.528      3.098
min        NaN    NaN       NaN      1.000    NaN      0.000      1.000
25%        NaN    NaN       NaN      8.000    NaN    103.000      1.000
50%        NaN    NaN       NaN     16.000    NaN    180.000      2.000
75%        NaN    NaN       NaN     21.000    NaN    319.000      3.000
max        NaN    NaN       NaN     31.000    NaN   4918.000     63.000

            pdays   previous poutcome      y
```

```
count   45211.000  45211.000    45211  45211
unique        NaN        NaN        4      2
top           NaN        NaN  unknown     no
freq          NaN        NaN    36959  39922
mean       40.198      0.580      NaN    NaN
std       100.129      2.303      NaN    NaN
min        -1.000      0.000      NaN    NaN
25%        -1.000      0.000      NaN    NaN
50%        -1.000      0.000      NaN    NaN
75%        -1.000      0.000      NaN    NaN
max       871.000    275.000      NaN    NaN
```

This dataset needs a lot of pre-processing ... also it displays a good mixture of categorical and numeric variables

age seems OK job has 12 values, let's check their frequency

seems OK

```
In [8]: deposit.job.value_counts()
```

```
Out[8]: blue-collar      9732
        management       9458
        technician       7597
        admin.           5171
        services         4154
        retired          2264
        self-employed    1579
        entrepreneur     1487
        unemployed       1303
        housemaid        1240
        student           938
        unknown           288
        Name: job, dtype: int64
```

education has 4 values, let's check their frequency

seems OK

```
In [9]: deposit.education.value_counts()
```

```
Out[9]: secondary    23202
        tertiary     13301
        primary       6851
        unknown       1857
        Name: education, dtype: int64
```

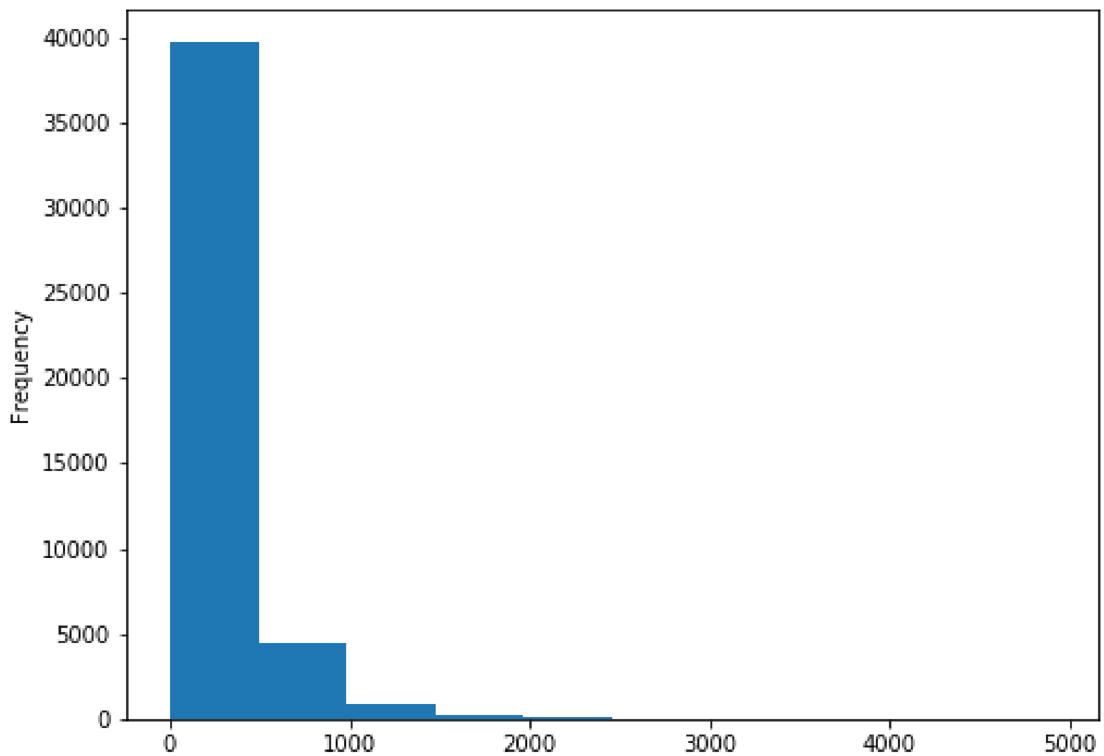
month looks very suspicious ... but is OK

```
In [10]: deposit.month.value_counts()
```

```
Out[10]: may    13766
         jul     6895
         aug     6247
         jun     5341
         nov     3970
         apr     2932
         feb     2649
         jan     1403
         oct      738
         sep      579
         mar      477
         dec      214
         Name: month, dtype: int64
```

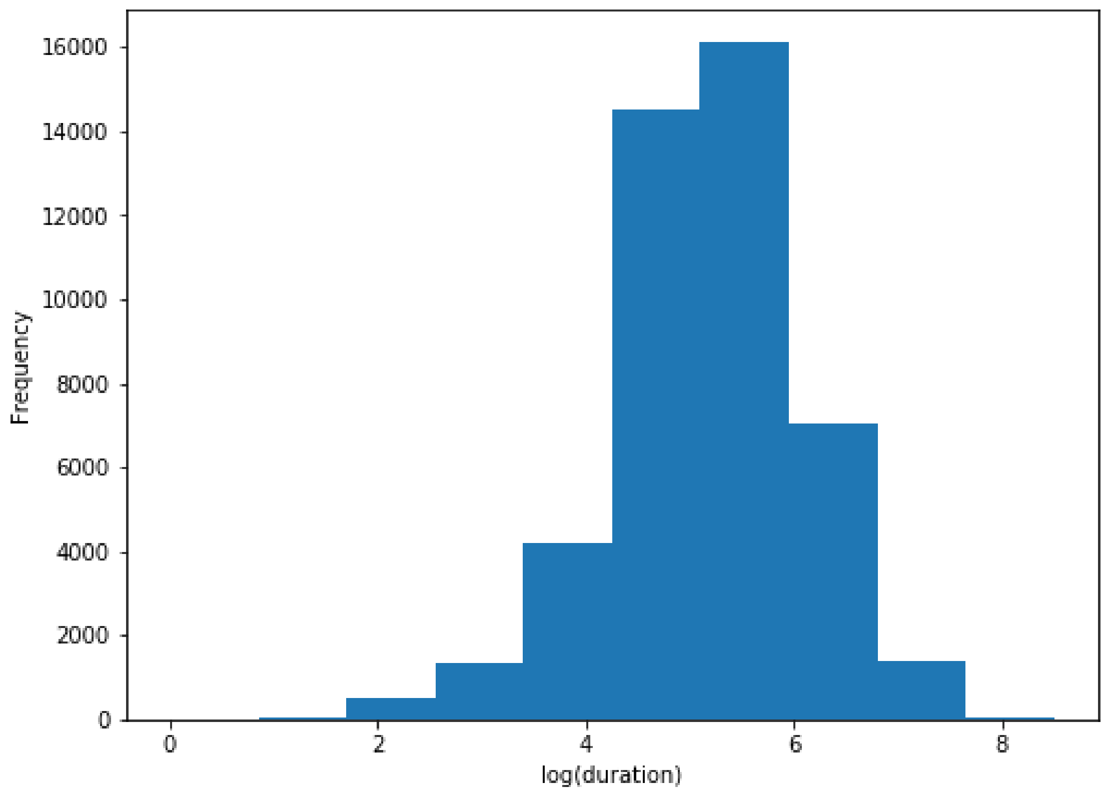
Duration is highly skewed ...

```
In [11]: deposit.duration.plot.hist(figsize=(8,6));
```




```
In [12]: pd.set_option('use_inf_as_na', True)
         ax = deposit.duration.apply('log').dropna().plot.hist(figsize=(8,6))
         plt.xlabel('log(duration)');
```

```
/usr/local/lib64/python3.6/site-packages/pandas/core/base.py:315: RuntimeWarning: divide by zero
  return f(self, *args, **kwargs)
```




```
In [13]: deposit['duration'] = deposit.duration.apply(lambda x: np.log(x+0.001))
```

what to do with 'pdays' and 'previous'? it is not clear how to best pre-process them; we shall need some financial expertise... we leave them as they are

The rest seem OK (but it would take a careful analysis, and a lot of domain knowledge)

Let's rename the target ...

```
In [14]: deposit.rename({'y':'subscribe'}, axis='columns',inplace=True)
         deposit.shape

Out[14]: (45211, 17)

In [15]: deposit.describe(include='all')

Out[15]:               age          job  marital  education default     balance  \
         count   45211.000        45211    45211      45211   45211   45211.000
         unique        NaN           12        3          4       2         NaN
         top           NaN  blue-collar  married  secondary      no         NaN
         freq          NaN         9732    27214      23202   44396         NaN
         mean       40.936          NaN      NaN        NaN     NaN    1362.272
         std        10.619          NaN      NaN        NaN     NaN    3044.766
         min        18.000          NaN      NaN        NaN     NaN   -8019.000
```

```
25%        33.000         NaN      NaN        NaN      NaN      72.000
50%        39.000         NaN      NaN        NaN      NaN     448.000
75%        48.000         NaN      NaN        NaN      NaN    1428.000
max        95.000         NaN      NaN        NaN      NaN  102127.000

       housing   loan   contact        day  month   duration   campaign  \
count    45211  45211     45211  45211.000  45211  45211.000  45211.000
unique       2      2         3        NaN     12        NaN        NaN
top        yes     no  cellular        NaN    may        NaN        NaN
freq     25130  37967     29285        NaN  13766        NaN        NaN
mean       NaN    NaN       NaN     15.806    NaN      5.162      2.764
std        NaN    NaN       NaN      8.322    NaN      0.938      3.098
min        NaN    NaN       NaN      1.000    NaN     -6.908      1.000
25%        NaN    NaN       NaN      8.000    NaN      4.635      1.000
50%        NaN    NaN       NaN     16.000    NaN      5.193      2.000
75%        NaN    NaN       NaN     21.000    NaN      5.765      3.000
max        NaN    NaN       NaN     31.000    NaN      8.501     63.000

            pdays   previous poutcome subscribe
count   45211.000  45211.000    45211     45211
unique        NaN        NaN        4         2
top           NaN        NaN  unknown        no
freq          NaN        NaN    36959     39922
mean       40.198      0.580      NaN       NaN
std       100.129      2.303      NaN       NaN
min        -1.000      0.000      NaN       NaN
25%        -1.000      0.000      NaN       NaN
50%        -1.000      0.000      NaN       NaN
75%        -1.000      0.000      NaN       NaN
max       871.000    275.000      NaN       NaN
```

Scikit learn decision trees classifier do not handle categorical attributes so we have to transform them to numerical

In [16]:
```
for v in deposit.columns:
    if deposit[v].dtype.kind == 'O':
        deposit[v] = LabelEncoder().fit_transform(deposit[v])

deposit.head()
```

Out[16]:
```
   age  job  marital  education  default  balance  housing  loan  contact  \
0   58    4        1          2        0     2143        1     0        2
1   44    9        2          1        0       29        1     0        2
2   33    2        1          1        0        2        1     1        2
3   47    1        1          3        0     1506        1     0        2
4   33   11        2          3        0        1        0     0        2

   day  month  duration  campaign  pdays  previous  poutcome  subscribe
```

0	5	8	5.565	1	-1	0	3	0
1	5	8	5.017	1	-1	0	3	0
2	5	8	4.331	1	-1	0	3	0
3	5	8	4.522	1	-1	0	3	0
4	5	8	5.288	1	-1	0	3	0

precalculate the TR/TE partition and the cross-validation partitions on the TR part

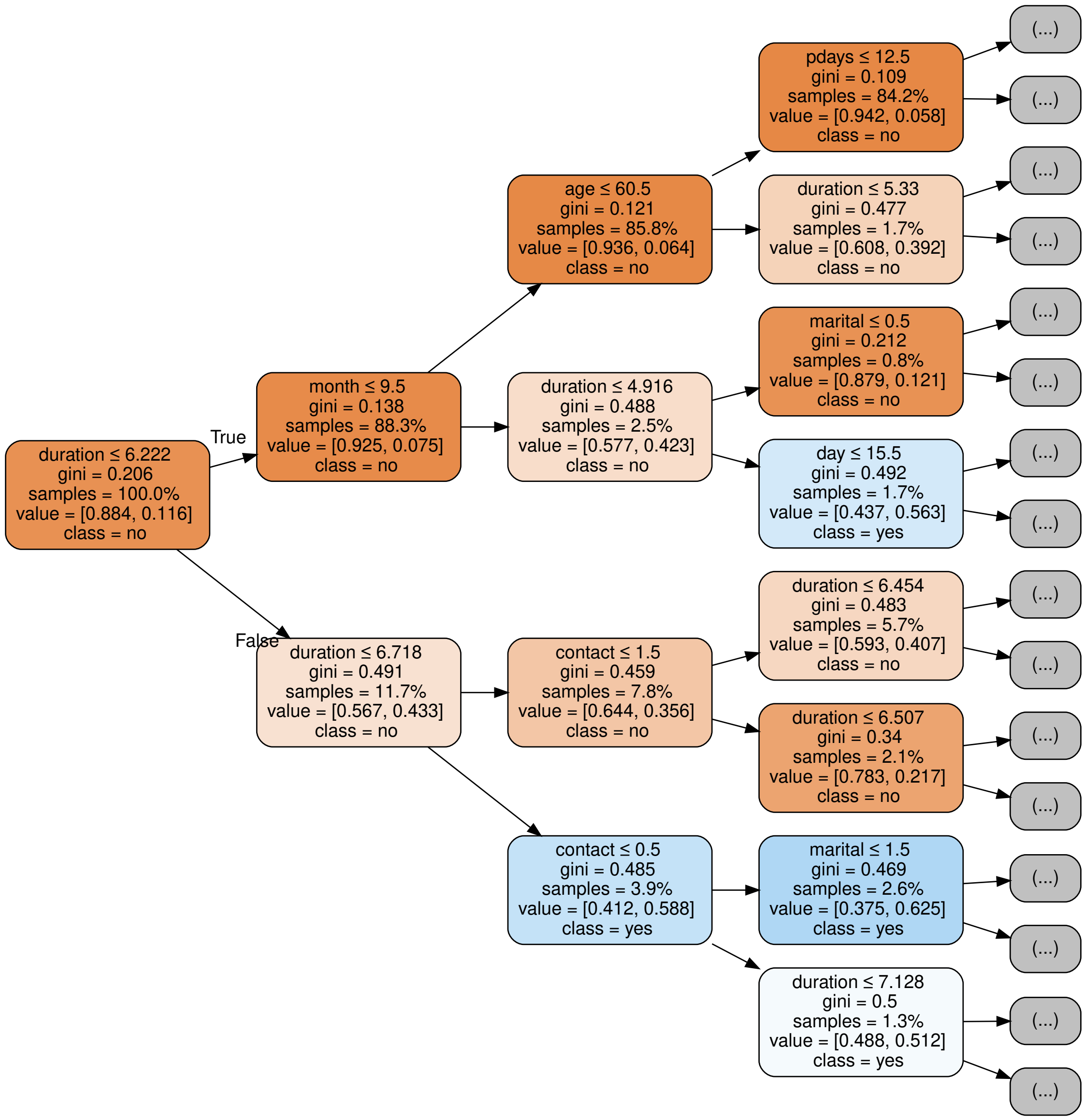
```
In [17]: train, test = train_test_split(deposit, test_size=1/3)
```

First try a standard decision tree.

```
In [18]: model_tree = DecisionTreeClassifier().fit(train.loc[:,:'poutcome'],
                                                   train.subscribe)
```

```
In [19]: dot_data = export_graphviz(model_tree, out_file=None,
                                    feature_names=deposit.columns[:-1],
                                    class_names=['no', 'yes'],
                                    filled=True, rounded=True,
                                    special_characters=True,
                                    rotate=True,
                                    proportion=True,
                                    max_depth=3)
         graph = graphviz.Source(dot_data)
         graph
```

Out[19]:




```
In [20]: pred = model_tree.predict(test.loc[:,:'poutcome'])

         confusion(test.subscribe,pred,['no','yes'])
```

```
Out[20]: Predicted     no    yes
         Actual
         no         12216   1073
         yes          943    839
```

prediction error

```
In [21]: (1-accuracy_score(test.subscribe,pred))*100
```

```
Out[21]: 13.376683697166747
```

F1 score

```
In [22]: f1_score(test.subscribe,pred)
```

```
Out[22]: 0.45425013535462916
```

From the detailed report we can see that the classification for the class yes is not very good

```
In [23]: print(classification_report(test.subscribe,
                                     pred,
                                     target_names=['no', 'yes'],))
```

```
             precision    recall  f1-score   support

         no       0.93      0.92      0.92     13289
        yes       0.44      0.47      0.45      1782

avg / total       0.87      0.87      0.87     15071
```

Now a random Forest

```
In [24]: model_rf1 = RandomForestClassifier(oob_score=True).fit(train.loc[:,:'poutcome'],
                                                                 train.subscribe)

         pred = model_rf1.predict(train.loc[:,:'poutcome'])

         confusion(train.subscribe,pred, ['no','yes'])

         print(classification_report(train.subscribe,
                                     pred,
                                     target_names=['no', 'yes'],))

         print('OOB error=', 1-model_rf1.oob_score_)
```

```
/home/bejar/.local/lib/python3.6/site-packages/sklearn/ensemble/forest.py:453: UserWarning: Some
  warn("Some inputs do not have OOB scores. "
/home/bejar/.local/lib/python3.6/site-packages/sklearn/ensemble/forest.py:458: RuntimeWarning: i
  predictions[k].sum(axis=1)[:, np.newaxis])
```

```
Out[24]: Predicted     no   yes
         Actual
         no         26628     5
         yes          247  3260
```

```
             precision    recall  f1-score   support

         no       0.99      1.00      1.00     26633
        yes       1.00      0.93      0.96      3507

avg / total       0.99      0.99      0.99     30140

OOB error= 0.10776376907763774
```

We get now a better estimated test error (OOB)
let's compute the real test error:

```
In [25]: pred = model_rf1.predict(test.loc[:,:'poutcome'])

         confusion(test.subscribe,pred, ['no','yes'])
```

```
Out[25]: Predicted     no  yes
         Actual
         no         12890  399
         yes         1095  687
```

Error

```
In [26]: (1-accuracy_score(test.subscribe,pred))*100
```

```
Out[26]: 9.9130780970075
```

F1 score

```
In [27]: f1_score(test.subscribe,pred)
```

```
Out[27]: 0.4790794979079498
```

```
In [28]: print(classification_report(test.subscribe,
                                     pred,
                                     target_names=['no', 'yes'],))
```

```
             precision    recall  f1-score   support

         no       0.92      0.97      0.95     13289
        yes       0.63      0.39      0.48      1782

avg / total       0.89      0.90      0.89     15071
```

So OOB really works in estimating prediction error and the RF is better than a single tree; however, there is a big issue in unbalanced classes

one way to deal with this is to include class weights

```
In [29]: model_rf2 = RandomForestClassifier(n_estimators=100,
                                           oob_score=True,
                                           class_weight={0:1,1:10}).fit(train.loc[:,:'poutcome'
                                                                  train.subscribe)


         pred = model_rf2.predict(train.loc[:,:'poutcome'])

         confusion(train.subscribe,pred, ['no','yes'])

         print(classification_report(train.subscribe,pred,target_names=['no', 'yes'],))

         print('OOB error=', 1- model_rf2.oob_score_)
```

```
Out[29]: Predicted     no   yes
         Actual
         no          26633     0
         yes             1  3506

             precision    recall  f1-score   support

         no       1.00      1.00      1.00     26633
        yes       1.00      1.00      1.00      3507

avg / total       1.00      1.00      1.00     30140

OOB error= 0.10066357000663573
```

which helps a little bit, but not much: with a better balance; let's compute the real test error:

```
In [30]: pred = model_rf2.predict(test.loc[:,:'poutcome'])

         confusion(test.subscribe,pred,['no','yes'])
```

```
Out[30]: Predicted     no  yes
         Actual
         no          12996  293
         yes          1178  604
```

```
In [31]: (1-accuracy_score(test.subscribe,pred))*100
```

```
Out[31]: 9.760467122287842
```

```
In [32]: f1_score(test.subscribe,pred)
```

```
Out[32]: 0.4509145203434118
```

```
In [33]: print(classification_report(test.subscribe,
                                     pred,
                                     target_names=['no', 'yes'],))
```

```
             precision    recall  f1-score   support

         no       0.92      0.98      0.95     13289
        yes       0.67      0.34      0.45      1782

avg / total       0.89      0.90      0.89     15071
```

another way is to balance the sampling in the boostrap resamples

'no' is the more represented class, so we down sample it

scikit-learn does not provide resample algorithms, but we can use the imbalanced-learn library that provides many strategies for kind of problem.

We resample the training so the number of `yes` examples equals the number of `no` examples

```
In [34]: rus = RandomUnderSampler()
         X_resampled, y_resampled = rus.fit_sample(train.loc[:,:'poutcome'],
                                                   train.subscribe)
         X_resampled.shape
```

```
Out[34]: (7014, 16)
```

```
In [35]: model_rf3 = RandomForestClassifier(n_estimators=100,
                                            oob_score=True).fit(X_resampled,
                                                                y_resampled)

         pred = model_rf3.predict(train.loc[:,:'poutcome'])

         confusion(train.subscribe,pred, ['no','yes'])

         print(classification_report(train.subscribe,
                                     pred,
                                     target_names=['no', 'yes'],))

         print('OOB error=', 1- model_rf3.oob_score_)
```

```
Out[35]: Predicted     no   yes
         Actual
         no         22574  4059
         yes            0  3507

             precision    recall  f1-score   support

         no       1.00      0.85      0.92     26633
        yes       0.46      1.00      0.63      3507

avg / total       0.94      0.87      0.88     30140

OOB error= 0.14556601083547194
```

which seems to help much more for balancing the yes class
let's compute the real test error:

```
In [36]: pred = model_rf3.predict(test.loc[:,:'poutcome'])

         confusion(test.subscribe,pred, ['no','yes'])

Out[36]: Predicted     no   yes
         Actual
         no         10921  2368
         yes          200  1582

In [37]: (1-accuracy_score(test.subscribe,pred))*100

Out[37]: 17.039347090438596

In [38]: f1_score(test.subscribe,pred)

Out[38]: 0.5519888346127005

In [39]: print(classification_report(test.subscribe,
                                     pred,
                                     target_names=['no', 'yes'],))

             precision    recall  f1-score   support

         no       0.98      0.82      0.89     13289
        yes       0.40      0.89      0.55      1782

avg / total       0.91      0.83      0.85     15071
```

Now we can try to optimize the number of trees, guided by OOB:

```
In [40]: ntrees = np.array(np.round(10**np.arange(1,3.1,0.2)),dtype=int)
         ntrees

Out[40]: array([  10,   16,   25,   40,   63,  100,  158,  251,  398,  631, 1000])

In [41]: rf_results= []
         for nt in ntrees:
             model_rf = RandomForestClassifier(n_estimators=nt,
                                               oob_score=True).fit(X_resampled, y_resampled)
             rf_results.append(1-model_rf.oob_score_)

         rf_results = pd.DataFrame({'ntrees':ntrees, 'OOB':rf_results})
```

```
/home/bejar/.local/lib/python3.6/site-packages/sklearn/ensemble/forest.py:453: UserWarning: Some
  warn("Some inputs do not have OOB scores. "
/home/bejar/.local/lib/python3.6/site-packages/sklearn/ensemble/forest.py:458: RuntimeWarning: i
  predictions[k].sum(axis=1)[:, np.newaxis])
/home/bejar/.local/lib/python3.6/site-packages/sklearn/ensemble/forest.py:453: UserWarning: Some
  warn("Some inputs do not have OOB scores. "
/home/bejar/.local/lib/python3.6/site-packages/sklearn/ensemble/forest.py:458: RuntimeWarning: i
  predictions[k].sum(axis=1)[:, np.newaxis])
```

```
In [42]: rf_results
```

Out[42]:

	ntrees	OOB
0	10	0.210
1	16	0.175
2	25	0.172
3	40	0.157
4	63	0.150
5	100	0.150
6	158	0.148
7	251	0.147
8	398	0.146
9	631	0.145
10	1000	0.145

choose best value of 'ntrees'

```
In [43]: rf_results.loc[rf_results.OOB.idxmin]
```

```
Out[43]: ntrees    631.000
         OOB         0.145
         Name: 9, dtype: float64
```

we could also try to optimize the number of variables in the same way, though the default values work quite well in general

Now refit the RF with the best value of 'ntrees'

```
In [44]: model_rf = RandomForestClassifier(n_estimators=rf_results.ntrees.loc[rf_results.OOB.idx
                                           oob_score=True).fit(X_resampled,
                                                               y_resampled)
```

let's compute the real test error:

```
In [45]: pred = model_rf.predict(test.loc[:,:'poutcome'])

         confusion(test.subscribe,pred, ['no','yes'])
```

```
Out[45]: Predicted     no   yes
         Actual
         no         10883  2406
         yes          198  1584
```

In [46]: (1-accuracy_score(test.subscribe,pred))*100

Out[46]: 17.27821644217371

In [47]: f1_score(test.subscribe,pred)

Out[47]: 0.5488565488565488

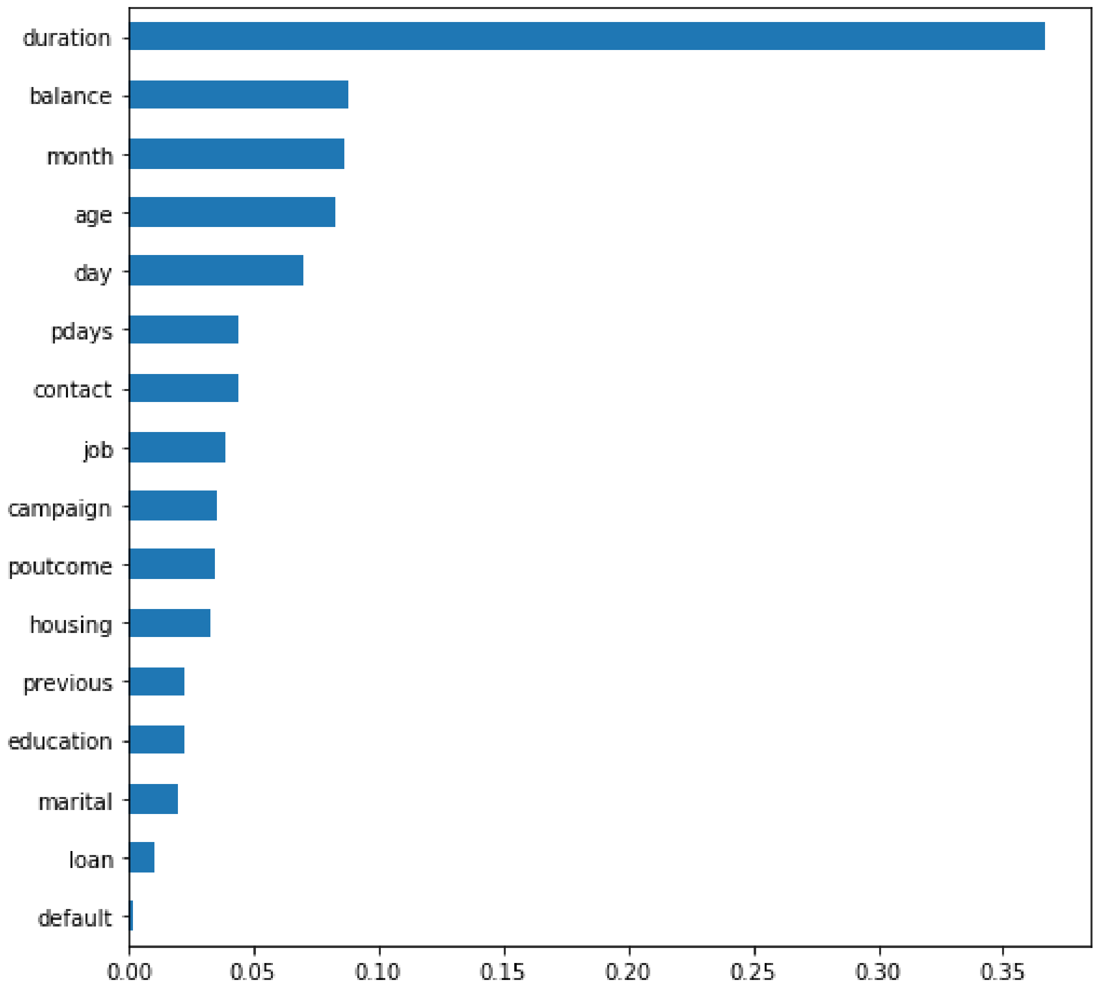
In [48]: print(classification_report(test.subscribe,
                                    pred,
                                    target_names=['no', 'yes']))

```
             precision    recall  f1-score   support

         no       0.98      0.82      0.89     13289
        yes       0.40      0.89      0.55      1782

avg / total       0.91      0.83      0.85     15071
```

The importance of variables

In [49]: var_imp = pd.DataFrame({'importance': model_rf.feature_importances_},
                               index=deposit.columns[:-1])

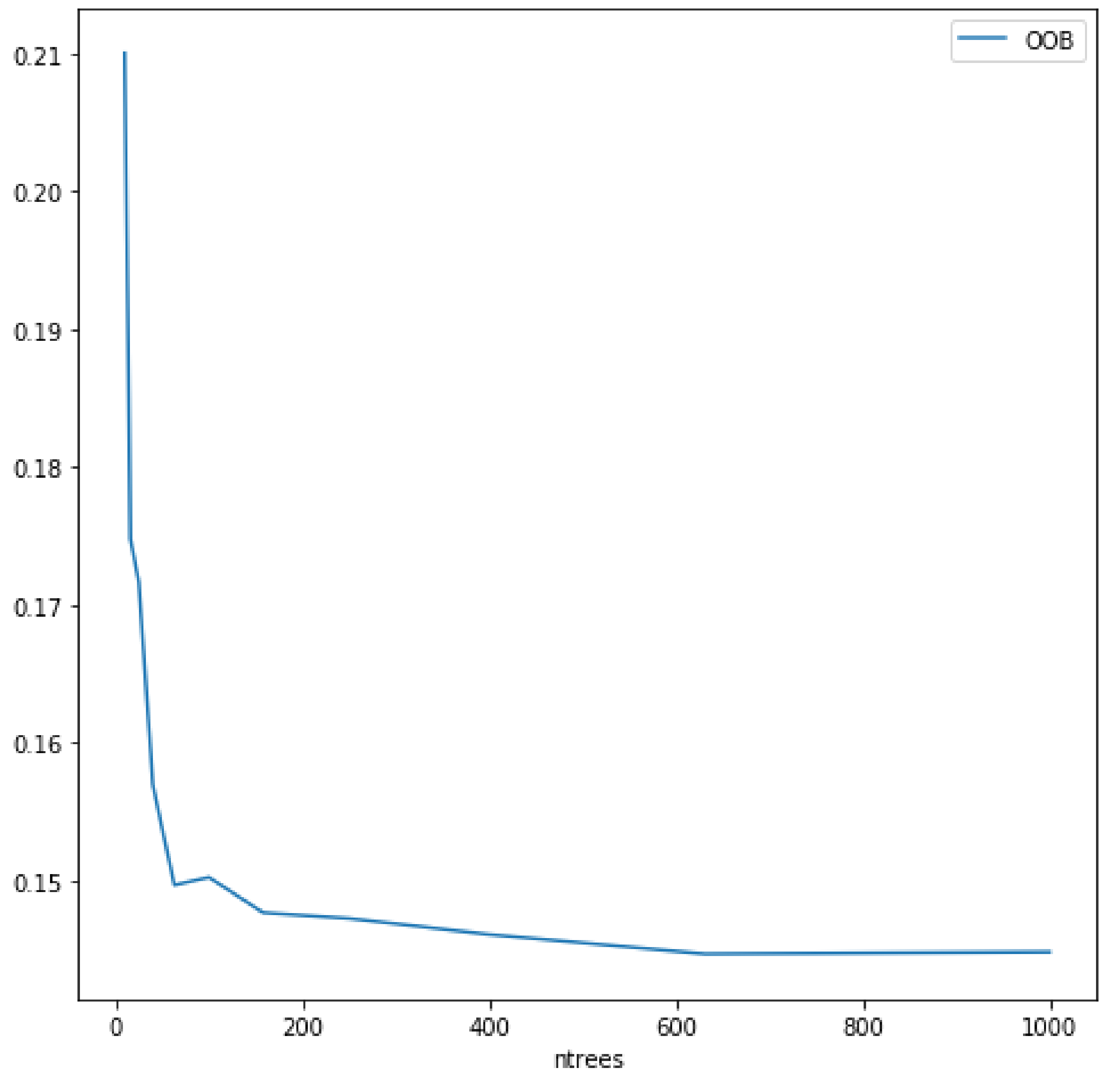
In [50]: var_imp.sort_values(by='importance').plot.barh(figsize=(8,8),
                                                       legend=False);



'duration' is the most important variable

plot error rate: black = out of bag (OOB), red = label 1 ('no'), green = label 2 ('yes') as a function of the number of trees used

```
In [51]: rf_results.plot(x='ntrees',y='OOB',figsize=(8,8));
```


OOB
0.21
0.20
0.19
0.18
0.17
0.16
0.15
0
200
400
600
800
1000
ntrees