Triple Barrier Method

This notebook will cover partial exercise answers:

- Exercise 3.5

As we go along, there will be some explanations.

More importantly, this method can be applied not just within mean-reversion strategy but also other strategies as well.

Most of the functions below can be found under research/Labels.

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In [1]:
```
import numpy as np
import pandas as pd
import research as rs
import matplotlib.pyplot as plt

%matplotlib inline

p = print

#pls take note of version
#numpy 1.17.3
#pandas 1.0.3
#sklearn 0.21.3

dollar = pd.read_csv('./research/Sample_data/dollar_bars.txt',
                 sep=',',
                 header=0,
                 parse_dates = True,
                 index_col=['date_time'])
```

```
Num of CPU core:  4
Machine info:  Windows-10-10.0.18362-SP0
Python 3.7.4 (default, Aug  9 2019, 18:34:13) [MSC v.1915 64 bit (AMD64)]
Numpy 1.17.3
Pandas 1.0.3
C:\Users\Wei_X\Anaconda3\lib\site-packages\statsmodels\tools\_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the p
ublic API at pandas.testing instead.
  import pandas.util.testing as tm
<Figure size 1500x800 with 1 Axes>
```

In [2]:
```
def bband(data: pd.DataFrame, window: int = 21, width: float = 0.001):
    avg = data['close'].ewm(span = window).mean()
    std = avg * width
```

```python
    upper = avg + std
    lower = avg - std
    return avg, upper, lower, std

dollar['ewm'], dollar['upper'], dollar['lower'], dollar['std'] = bband(dolla

# Check for normality, serial correlation, overall statistical properties, f
```

In [3]:
```python
dollar['side'] = np.nan

def side_pick(data: pd.DataFrame):
    for i in np.arange(data.index.shape[0]):
        if (data['close'].iloc[i] >= data['upper'].iloc[i]):
            data['side'].iat[i] = -1
        elif (data['close'].iloc[i] <= data['lower'].iloc[i]):
            data['side'].iat[i] = 1
    return data

upper = dollar[dollar['upper'] < dollar['close']] # short signal
lower = dollar[dollar['lower'] > dollar['close']] # long signal

p("Num of times upper limit touched: {0}\nNum of times lower limit touched:
  .format(upper.count()[0],
          lower.count()[0]))

# Recall white test as a benchmark and until this stage we filtered all thos
dollar = side_pick(dollar)
dollar.dropna(inplace= True)
dollar['side'].value_counts()
```

```
Num of times upper limit touched: 8495
Num of times lower limit touched: 7811
```

Out[3]:
```
-1.0    8495
 1.0    7811
Name: side, dtype: int64
```

In [4]:
```python
copy_dollar = dollar.copy() # make a back copy to be used in later exercise

copy_dollar #up till this point the below dataframe should look like this, b
```

Out[4]:

date_time	open	high	low	close	cum_vol	cum_dollar	cum_ticks
2015-01-02 07:07:35.156	2056.75	2067.25	2056.25	2064.00	33968	70010061.25	14514
2015-01-02 14:19:33.847	2061.00	2064.25	2058.75	2063.75	33958	70000723.25	12332
2015-01-02 14:33:39.311	2063.75	2064.75	2060.00	2064.50	33944	70001009.00	12846
2015-01-02 14:42:28.315	2064.50	2066.50	2063.25	2066.00	33901	70010093.25	13032
2015-01-02 15:01:45.497	2063.50	2064.00	2058.75	2058.75	34008	70122046.75	13873
...	...	...	...	...	...	...	...
2016-12-30 20:22:33.456	2231.25	2233.75	2231.00	2233.50	31355	70001983.50	2453
2016-12-30 20:32:57.188	2233.50	2235.00	2232.50	2233.25	31349	70029302.00	2621
2016-12-30 20:44:21.481	2233.25	2234.00	2230.50	2230.75	31362	70017565.50	2836
2016-12-30 20:50:57.567	2230.75	2231.75	2229.25	2229.75	31386	70009159.50	2101
2016-12-30 20:55:33.160	2229.75	2231.25	2229.25	2231.00	31399	70020888.50	2017

16306 rows × 12 columns

In [5]:

```
d_vol = rs.vol(dollar['close'], span0 = 50)
```

In [6]:

```
events = rs.cs_filter(dollar['close'],
                      limit = d_vol.mean())

events
```

Out[6]:
```
DatetimeIndex(['2015-01-02 14:19:33.847000', '2015-01-02 14:33:39.311000',
               '2015-01-02 14:42:28.315000', '2015-01-02 15:01:45.497000',
               '2015-01-02 15:22:54.187000', '2015-01-02 15:32:59.861000',
               '2015-01-02 15:39:14.826000', '2015-01-02 15:43:25.099000',
               '2015-01-02 15:48:54.420000', '2015-01-02 15:57:26.907000',
               ...
               '2016-12-30 19:02:57.783000', '2016-12-30 19:29:47.411000',
               '2016-12-30 19:47:05.557000', '2016-12-30 19:55:31.030000',
               '2016-12-30 20:12:10.314000', '2016-12-30 20:22:33.456000',
               '2016-12-30 20:32:57.188000', '2016-12-30 20:44:21.481000',
               '2016-12-30 20:50:57.567000', '2016-12-30 20:55:33.160000'],
              dtype='datetime64[ns]', length=15459, freq=None)
```

In [7]:
```
vb = rs.vert_barrier(data = dollar['close'],
                 events = events,
                 period = 'days',
                 freq = 1)

vb # Show some example output
```

Out[7]:
```
2015-01-02 14:19:33.847   2015-01-04 23:20:12.567
2015-01-02 14:33:39.311   2015-01-04 23:20:12.567
2015-01-02 14:42:28.315   2015-01-04 23:20:12.567
2015-01-02 15:01:45.497   2015-01-04 23:20:12.567
2015-01-02 15:22:54.187   2015-01-04 23:20:12.567
                                   ...
2016-12-29 16:18:10.918   2016-12-30 17:17:03.543
2016-12-29 16:43:29.395   2016-12-30 17:17:03.543
2016-12-29 17:03:04.248   2016-12-30 17:17:03.543
2016-12-29 17:17:04.110   2016-12-30 17:44:08.768
2016-12-29 18:58:02.400   2016-12-30 19:02:57.783
Name: date_time, Length: 15434, dtype: datetime64[ns]
```

In [8]:
```
tb = rs.tri_barrier(data = dollar['close'],
                events = events,
                trgt = d_vol,
                min_req = 0.002,
                num_threads = 3,
                ptSl = [0,2], #change ptSl into [0,2]
                t1 = vb,
                side = dollar['side'])

tb # Show some example
```

```
C:\Users\Wei_X\Desktop\Python\research\Labels\triple_barrier_method.py:75: U
serWarning: Data and events index shape must be same, reindex data to fit ev
ents
  warnings.warn('Data and events index shape must be same, reindex data to f
it events')
[                                              t1                        sl  pt
2015-01-05 14:54:26.286 2015-01-06 15:16:04.445 2015-01-05 16:15:59.512 NaT
2015-01-05 14:57:13.616 2015-01-06 15:16:04.445 2015-01-05 16:21:16.062 NaT
2015-01-05 15:01:57.494 2015-01-06 15:16:04.445 2015-01-05 17:32:22.888 NaT
```

```
2015-01-05 15:07:29.012 2015-01-06 15:16:04.445 2015-01-05 17:26:59.327 NaT
2015-01-05 15:13:09.655 2015-01-06 15:16:04.445 2015-01-05 17:32:22.888 NaT
...                                             ...                     ...  ..
2015-09-09 08:33:28.634 2015-09-10 09:33:29.450                         NaT NaT
2015-09-09 10:21:19.955 2015-09-10 11:43:14.539                         NaT NaT
2015-09-09 12:02:05.852 2015-09-10 12:19:25.229                         NaT NaT
2015-09-09 13:06:01.330 2015-09-10 13:30:20.359                         NaT NaT
2015-09-09 13:31:24.524 2015-09-10 13:35:08.110                         NaT NaT

[5142 rows x 3 columns]] this out
[                                                 t1                      sl  pt
2015-01-05 14:54:26.286 2015-01-06 15:16:04.445 2015-01-05 16:15:59.512 NaT
2015-01-05 14:57:13.616 2015-01-06 15:16:04.445 2015-01-05 16:21:16.062 NaT
2015-01-05 15:01:57.494 2015-01-06 15:16:04.445 2015-01-05 17:32:22.888 NaT
2015-01-05 15:07:29.012 2015-01-06 15:16:04.445 2015-01-05 17:26:59.327 NaT
2015-01-05 15:13:09.655 2015-01-06 15:16:04.445 2015-01-05 17:32:22.888 NaT
...                                             ...                     ...  ..
2015-09-09 08:33:28.634 2015-09-10 09:33:29.450                         NaT NaT
2015-09-09 10:21:19.955 2015-09-10 11:43:14.539                         NaT NaT
2015-09-09 12:02:05.852 2015-09-10 12:19:25.229                         NaT NaT
2015-09-09 13:06:01.330 2015-09-10 13:30:20.359                         NaT NaT
2015-09-09 13:31:24.524 2015-09-10 13:35:08.110                         NaT NaT

[5142 rows x 3 columns],                                                 t1  sl
pt
2015-09-09 13:36:53.472 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:40:56.133 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:45:08.189 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:51:11.450 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 14:02:04.210 2015-09-10 14:05:19.003 NaT NaT
...                                             ...  ..  ..
2016-04-05 01:16:26.261 2016-04-06 02:45:07.823 NaT NaT
2016-04-05 06:02:04.305 2016-04-06 07:07:24.337 NaT NaT
2016-04-05 07:11:07.085 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 07:37:56.273 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 08:24:13.547 2016-04-06 09:05:34.702 NaT NaT

[5142 rows x 3 columns]] this out
[                                                 t1                      sl  pt
2015-01-05 14:54:26.286 2015-01-06 15:16:04.445 2015-01-05 16:15:59.512 NaT
2015-01-05 14:57:13.616 2015-01-06 15:16:04.445 2015-01-05 16:21:16.062 NaT
2015-01-05 15:01:57.494 2015-01-06 15:16:04.445 2015-01-05 17:32:22.888 NaT
2015-01-05 15:07:29.012 2015-01-06 15:16:04.445 2015-01-05 17:26:59.327 NaT
2015-01-05 15:13:09.655 2015-01-06 15:16:04.445 2015-01-05 17:32:22.888 NaT
...                                             ...                     ...  ..
2015-09-09 08:33:28.634 2015-09-10 09:33:29.450                         NaT NaT
2015-09-09 10:21:19.955 2015-09-10 11:43:14.539                         NaT NaT
2015-09-09 12:02:05.852 2015-09-10 12:19:25.229                         NaT NaT
2015-09-09 13:06:01.330 2015-09-10 13:30:20.359                         NaT NaT
2015-09-09 13:31:24.524 2015-09-10 13:35:08.110                         NaT NaT

[5142 rows x 3 columns],                                                 t1  sl
pt
```

```
2015-09-09 13:36:53.472 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:40:56.133 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:45:08.189 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:51:11.450 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 14:02:04.210 2015-09-10 14:05:19.003 NaT NaT
...                                            ...  ..  ..
2016-04-05 01:16:26.261 2016-04-06 02:45:07.823 NaT NaT
2016-04-05 06:02:04.305 2016-04-06 07:07:24.337 NaT NaT
2016-04-05 07:11:07.085 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 07:37:56.273 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 08:24:13.547 2016-04-06 09:05:34.702 NaT NaT

[5142 rows x 3 columns],                                                    t1  sl
pt
2016-04-05 09:17:57.890 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 10:11:56.123 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 11:26:40.687 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 12:10:26.367 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 12:55:36.469 2016-04-06 13:14:38.661 NaT NaT
...                                            ...  ..  ..
2016-12-30 20:22:33.456                     NaT NaT NaT
2016-12-30 20:32:57.188                     NaT NaT NaT
2016-12-30 20:44:21.481                     NaT NaT NaT
2016-12-30 20:50:57.567                     NaT NaT NaT
2016-12-30 20:55:33.160                     NaT NaT NaT

[5141 rows x 3 columns]] this out
```

```
2020-05-24 19:47:10.399688 33.33% _pt_sl_t1 done after 0.38 minutes. Remaini
ng 0.76 minutes.
2020-05-24 19:47:10.399688 66.67% _pt_sl_t1 done after 0.38 minutes. Remaini
ng 0.19 minutes.
2020-05-24 19:47:10.493415 100.0% _pt_sl_t1 done after 0.38 minutes. Remaini
ng 0.0 minutes.
```

Out[8]:

	t1	trgt	side
2015-01-05 14:54:26.286	2015-01-05 16:15:59.512	0.002238	1.0
2015-01-05 14:57:13.616	2015-01-05 16:21:16.062	0.002462	1.0
2015-01-05 15:01:57.494	2015-01-05 17:32:22.888	0.002779	1.0
2015-01-05 15:07:29.012	2015-01-05 17:26:59.327	0.002819	1.0
2015-01-05 15:13:09.655	2015-01-05 17:32:22.888	0.002874	1.0
...	...	...	...
2016-12-29 16:18:10.918	2016-12-30 17:17:03.543	0.004250	1.0
2016-12-29 16:43:29.395	2016-12-30 17:17:03.543	0.004166	1.0
2016-12-29 17:03:04.248	2016-12-30 17:17:03.543	0.004090	1.0
2016-12-29 17:17:04.110	2016-12-30 17:44:08.768	0.004016	1.0
2016-12-29 18:58:02.400	2016-12-30 19:02:57.783	0.003979	1.0

15400 rows × 3 columns

In [9]:

```
m_label = rs.meta_label(data = dollar['close'],
                        events = tb,
                        drop = False)

m_label # Show some example
```

Out[9]:

	ret	bin	side
2015-01-05 14:54:26.286	-0.004556	0.0	1.0
2015-01-05 14:57:13.616	-0.005051	0.0	1.0
2015-01-05 15:01:57.494	-0.005798	0.0	1.0
2015-01-05 15:07:29.012	-0.005790	0.0	1.0
2015-01-05 15:13:09.655	-0.006656	0.0	1.0
...	...	...	...
2016-12-29 16:18:10.918	-0.001672	0.0	1.0
2016-12-29 16:43:29.395	-0.001894	0.0	1.0
2016-12-29 17:03:04.248	-0.001226	0.0	1.0
2016-12-29 17:17:04.110	-0.001450	0.0	1.0
2016-12-29 18:58:02.400	-0.002899	0.0	1.0

15400 rows × 3 columns

In [10]:
```
m_label['bin'].value_counts(normalize=True)

# Here is a quick look at our 'bin' values.
# Slight imbalanced sample, but not much harm
# 51.95% of the sample based on parameter touched vertical barrier first
```

Out[10]:
```
0.0    0.519545
1.0    0.480455
Name: bin, dtype: float64
```

- Exercise 3.5b

Here onwards we will be using sklearn modules to perform ML related task.

In [11]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split

# A quick look at what we have till date using both primary and secondary mo
# as seen in previous example, only 48.04% was labeled 1.
# Hence precision 1.0 = 0.48 (48% of the sample is relevant), while recall =
```

The below function report_matrix is what we have till date using both primary (bband func) and secondary model (tri_bar func).

Classification Report

As seen in previous example, only 48.0455% was labeled 1.

Hence precision 1.0 = 0.48 (48.0455% of the sample is relevant). It's basically ML's way of saying are these "features" relevant when tested.

While recall = 1 means fully correct (based on the 48% sample). In the case where ML model is fitted, this result will mean the percentage of "correct" label was chosen. In short, is the ML model reliability in True positive identification based on given sample.

Confusion Matrix

8001 = False Positive (51.95%) 7399 = True Positive (48.0455%)

Accuracy Score

Is a mere reflection of True Positive, which again is 48.0455%

In [12]:
```
# this func can be found under Tools/stats_rpt

forecast = rs.report_matrix(actual_data = m_label,
                            prediction_data = None,
                            ROC = None)
```

```
 Classification Report
=======================================================
              precision    recall  f1-score   support

         0.0       0.00      0.00      0.00      8001
         1.0       0.48      1.00      0.65      7399

    accuracy                           0.48     15400
   macro avg       0.24      0.50      0.32     15400
weighted avg       0.23      0.48      0.31     15400


 Confusion Matrix
=======================================================
[[TN, FP]
 [FN, TP]]

[[   0 8001]
 [   0 7399]]

 Accuracy Score
=======================================================
0.48045454545454547
```

```
C:\Users\Wei_X\Anaconda3\lib\site-packages\sklearn\metrics\classification.p
y:1437: UndefinedMetricWarning: Precision and F-score are ill-defined and be
ing set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

Built a list of features.

1. Volatility
2. Autocorrelation
3. Moving average
4. log-price return (optional)
5. Stationary series based on cumulative sum log-price return (optional)

The last 2 items will be explained at AFML chapter 5, fractional differentiated features.

In [13]:
```
# Data that was copied earlier before tri_bar func, this is our primary mode

copy_dollar # Show example
```

Out[13]:

	open	high	low	close	cum_vol	cum_dollar	cum_ticks
date_time							
2015-01-02 07:07:35.156	2056.75	2067.25	2056.25	2064.00	33968	70010061.25	14514
2015-01-02 14:19:33.847	2061.00	2064.25	2058.75	2063.75	33958	70000723.25	12332
2015-01-02 14:33:39.311	2063.75	2064.75	2060.00	2064.50	33944	70001009.00	12846
2015-01-02 14:42:28.315	2064.50	2066.50	2063.25	2066.00	33901	70010093.25	13032
2015-01-02 15:01:45.497	2063.50	2064.00	2058.75	2058.75	34008	70122046.75	13873
...	...	...	...	...	...	...	...
2016-12-30 20:22:33.456	2231.25	2233.75	2231.00	2233.50	31355	70001983.50	2453
2016-12-30 20:32:57.188	2233.50	2235.00	2232.50	2233.25	31349	70029302.00	2621
2016-12-30 20:44:21.481	2233.25	2234.00	2230.50	2230.75	31362	70017565.50	2836
2016-12-30 20:50:57.567	2230.75	2231.75	2229.25	2229.75	31386	70009159.50	2101
2016-12-30 20:55:33.160	2229.75	2231.25	2229.25	2231.00	31399	70020888.50	2017

16306 rows × 12 columns

In [14]:

```
# drop redundant columns and keep crossing moving avaerages
pri_dollar = copy_dollar.drop(['open', 'high', 'low', 'cum_vol', 'cum_dollar

#include volatility, autocorrelation
pri_dollar
```

Out[14]:

date_time	close	ewm	upper	lower	std	side
2015-01-02 07:07:35.156	2064.00	2060.547619	2062.608167	2058.487071	2.060548	-1.0
2015-01-02 14:19:33.847	2063.75	2061.404789	2063.466193	2059.343384	2.061405	-1.0
2015-01-02 14:33:39.311	2064.50	2062.050864	2064.112915	2059.988814	2.062051	-1.0
2015-01-02 14:42:28.315	2066.00	2062.788295	2064.851084	2060.725507	2.062788	-1.0
2015-01-02 15:01:45.497	2058.75	2062.252963	2064.315216	2060.190710	2.062253	1.0
...	...	...	...	...	...	...
2016-12-30 20:22:33.456	2233.50	2237.134042	2239.371176	2234.896908	2.237134	1.0
2016-12-30 20:32:57.188	2233.25	2236.780947	2239.017728	2234.544167	2.236781	1.0
2016-12-30 20:44:21.481	2230.75	2236.232680	2238.468912	2233.996447	2.236233	1.0
2016-12-30 20:50:57.567	2229.75	2235.643345	2237.878988	2233.407702	2.235643	1.0
2016-12-30 20:55:33.160	2231.00	2235.221223	2237.456444	2232.986002	2.235221	1.0

16306 rows × 6 columns

In [15]:

```
#include original volatility
pri_dollar['volatility'] = rs.vol(pri_dollar.close, span0 = 50)
```

In [16]:

```
# Optional: getting stationarity feature
pri_dollar['log_price'] = pri_dollar.close.apply(np.log)
pri_dollar['log_return'] = pri_dollar.log_price.diff()

cs_log = pri_dollar.log_price.diff().dropna().to_frame()
pri_dollar['stationary'] = rs.fracDiff_FFD(data = cs_log, d = 1.99999889 , t

rs.unit_root(pri_dollar['stationary'].dropna()) #check for stationarity
```

```
C:\Users\Wei_X\Desktop\Python\research\Features\fractional_diff.py:93: UserW
arning: thres val <= 1.e-2 may not suit non-trend series, may take up longer
than expected to calculate val i.e. 1e-5
  warnings.warn('thres val <= 1.e-2 may not suit non-trend series, may take
up longer than expected to calculate val i.e. 1e-5')
```

```
ADF & KPSS: Weak evidence for stationary
```

```
C:\Users\Wei_X\Anaconda3\lib\site-packages\statsmodels\tsa\stattools.py:168
5: FutureWarning: The behavior of using lags=None will change in the next re
lease. Currently lags=None is the same as lags='legacy', and so a sample-siz
e lag length is used. After the next release, the default will change to be
the same as lags='auto' which uses an automatic lag length selection method.
To silence this warning, either use 'auto' or 'legacy'
  warn(msg, FutureWarning)
C:\Users\Wei_X\Anaconda3\lib\site-packages\statsmodels\tsa\stattools.py:171
0: InterpolationWarning: p-value is greater than the indicated p-value
  warn("p-value is greater than the indicated p-value", InterpolationWarnin
g)
```

In [17]:

```
pri_dollar.dropna(inplace = True)
```

In [18]:

```
# autocorrelation residual feature, we will add AR features up to 2 lags
from statsmodels.tsa.arima_model import ARMA

pri_dollar['ar_0'] = ARMA(pri_dollar['stationary'], order=(0,0)).fit().resic
pri_dollar['ar_1'] = ARMA(pri_dollar['stationary'], order=(1,0)).fit().resic
pri_dollar['ar_2'] = ARMA(pri_dollar['stationary'], order=(2,0)).fit().resic
```

```
C:\Users\Wei_X\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.p
y:219: ValueWarning: A date index has been provided, but it has no associate
d frequency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
C:\Users\Wei_X\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.p
y:219: ValueWarning: A date index has been provided, but it has no associate
d frequency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
C:\Users\Wei_X\Anaconda3\lib\site-packages\statsmodels\base\model.py:512: Co
nvergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  "Check mle_retvals", ConvergenceWarning)
C:\Users\Wei_X\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.p
y:219: ValueWarning: A date index has been provided, but it has no associate
d frequency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
```

In [19]:

```
#final dataset

secondary_dollar = pri_dollar.copy()
```

**Note

- Good to include volume based or volume-weighted indicator as a predictive feature i.e. OBV, VWAP

Note

May try to add other types of trend related features as part of experimental

Mathematics. (aka Trial & error)

- Good to include volume based or volume-weighted indicator as a predictive feature i.e. OBV, VWAP
- If not, try to add price based as predictive feature i.e. MOM, RSI

In [20]:
```
# Now we run all the steps to complete labels, to train random forest.
# we will use both primary & secondary model

events0 = rs.cs_filter(secondary_dollar['close'],
                    limit = secondary_dollar['volatility'].mean())

vb0 = rs.vert_barrier(data = secondary_dollar['close'],
                  events = events0,
                  period = 'days',
                  freq = 1)

tb0 = rs.tri_barrier(data = secondary_dollar['close'],
                  events = events0,
                  trgt = secondary_dollar['volatility'],
                  min_req = 0.002,
                  num_threads = 3,
                  ptSl = [0,2], #change ptSl into [0,2]
                  t1 = vb0,
                  side = secondary_dollar['side'])

m_label0 = rs.meta_label(data = secondary_dollar['close'],
                      events = tb0,
                      drop = 0.05)

m_label0
```

```
C:\Users\Wei_X\Desktop\Python\research\Labels\triple_barrier_method.py:75: U
serWarning: Data and events index shape must be same, reindex data to fit ev
ents
  warnings.warn('Data and events index shape must be same, reindex data to f
it events')
```

```
[                                            t1  sl  pt
2015-09-09 13:36:53.472 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:40:56.133 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:45:08.189 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:51:11.450 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 14:02:04.210 2015-09-10 14:05:19.003 NaT NaT
...                                            ...  ..  ..
2016-04-05 01:16:26.261 2016-04-06 02:45:07.823 NaT NaT
2016-04-05 06:02:04.305 2016-04-06 07:07:24.337 NaT NaT
2016-04-05 07:11:07.085 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 07:37:56.273 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 08:24:13.547 2016-04-06 09:05:34.702 NaT NaT

[5142 rows x 3 columns]] this out
[                                            t1  sl  pt
2015-09-09 13:36:53.472 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:40:56.133 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:45:08.189 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:51:11.450 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 14:02:04.210 2015-09-10 14:05:19.003 NaT NaT
...                                            ...  ..  ..
2016-04-05 01:16:26.261 2016-04-06 02:45:07.823 NaT NaT
2016-04-05 06:02:04.305 2016-04-06 07:07:24.337 NaT NaT
2016-04-05 07:11:07.085 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 07:37:56.273 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 08:24:13.547 2016-04-06 09:05:34.702 NaT NaT

[5142 rows x 3 columns],                                                        t1
sl  pt
2015-01-05 14:54:26.286 2015-01-06 15:16:04.445 2015-01-05 16:15:59.512 NaT
2015-01-05 14:57:13.616 2015-01-06 15:16:04.445 2015-01-05 16:21:16.062 NaT
2015-01-05 15:01:57.494 2015-01-06 15:16:04.445 2015-01-05 17:32:22.888 NaT
2015-01-05 15:07:29.012 2015-01-06 15:16:04.445 2015-01-05 17:26:59.327 NaT
2015-01-05 15:13:09.655 2015-01-06 15:16:04.445 2015-01-05 17:32:22.888 NaT
...                                            ...                        ...  ..
2015-09-09 08:33:28.634 2015-09-10 09:33:29.450                        NaT NaT
2015-09-09 10:21:19.955 2015-09-10 11:43:14.539                        NaT NaT
2015-09-09 12:02:05.852 2015-09-10 12:19:25.229                        NaT NaT
2015-09-09 13:06:01.330 2015-09-10 13:30:20.359                        NaT NaT
2015-09-09 13:31:24.524 2015-09-10 13:35:08.110                        NaT NaT

[5142 rows x 3 columns]] this out
```

```
2020-05-24 19:47:44.210234 33.33% _pt_sl_t1 done after 0.38 minutes. Remaini
ng 0.75 minutes.
2020-05-24 19:47:44.303960 66.67% _pt_sl_t1 done after 0.38 minutes. Remaini
ng 0.19 minutes.
```

```
[                                            t1  sl  pt
2015-09-09 13:36:53.472 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:40:56.133 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:45:08.189 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:51:11.450 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 14:02:04.210 2015-09-10 14:05:19.003 NaT NaT
...                                           ...  ..  ..
2016-04-05 01:16:26.261 2016-04-06 02:45:07.823 NaT NaT
2016-04-05 06:02:04.305 2016-04-06 07:07:24.337 NaT NaT
2016-04-05 07:11:07.085 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 07:37:56.273 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 08:24:13.547 2016-04-06 09:05:34.702 NaT NaT

[5142 rows x 3 columns],                                                        t1
sl  pt
2015-01-05 14:54:26.286 2015-01-06 15:16:04.445 2015-01-05 16:15:59.512 NaT
2015-01-05 14:57:13.616 2015-01-06 15:16:04.445 2015-01-05 16:21:16.062 NaT
2015-01-05 15:01:57.494 2015-01-06 15:16:04.445 2015-01-05 17:32:22.888 NaT
2015-01-05 15:07:29.012 2015-01-06 15:16:04.445 2015-01-05 17:26:59.327 NaT
2015-01-05 15:13:09.655 2015-01-06 15:16:04.445 2015-01-05 17:32:22.888 NaT
...                                           ...                       ...  ..
2015-09-09 08:33:28.634 2015-09-10 09:33:29.450                     NaT NaT
2015-09-09 10:21:19.955 2015-09-10 11:43:14.539                     NaT NaT
2015-09-09 12:02:05.852 2015-09-10 12:19:25.229                     NaT NaT
2015-09-09 13:06:01.330 2015-09-10 13:30:20.359                     NaT NaT
2015-09-09 13:31:24.524 2015-09-10 13:35:08.110                     NaT NaT

[5142 rows x 3 columns],                                                        t1  sl
pt
2016-04-05 09:17:57.890 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 10:11:56.123 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 11:26:40.687 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 12:10:26.367 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 12:55:36.469 2016-04-06 13:14:38.661 NaT NaT
...                                           ...  ..  ..
2016-12-30 20:22:33.456                     NaT NaT NaT
2016-12-30 20:32:57.188                     NaT NaT NaT
2016-12-30 20:44:21.481                     NaT NaT NaT
2016-12-30 20:50:57.567                     NaT NaT NaT
2016-12-30 20:55:33.160                     NaT NaT NaT

[5141 rows x 3 columns]] this out
```

```
2020-05-24 19:47:44.834118 100.0% _pt_sl_t1 done after 0.39 minutes. Remaini
ng 0.0 minutes.
```

Out[20]:

	ret	bin	side
2015-01-05 14:54:26.286	-0.004556	0.0	1.0
2015-01-05 14:57:13.616	-0.005051	0.0	1.0
2015-01-05 15:01:57.494	-0.005798	0.0	1.0
2015-01-05 15:07:29.012	-0.005790	0.0	1.0
2015-01-05 15:13:09.655	-0.006656	0.0	1.0
...	...	...	...
2016-12-29 16:18:10.918	-0.001672	0.0	1.0
2016-12-29 16:43:29.395	-0.001894	0.0	1.0
2016-12-29 17:03:04.248	-0.001226	0.0	1.0
2016-12-29 17:17:04.110	-0.001450	0.0	1.0
2016-12-29 18:58:02.400	-0.002899	0.0	1.0

15400 rows × 3 columns

In [21]:

```
m_label0['bin'].value_counts()

# we still get back the same count. This is correct.
# Tri_bar func is to calculate if vert_bar was triggered and consolidates th
# while label will check which are the ones that hitted vertical barriers or
```

Out[21]:

```
0.0    8001
1.0    7399
Name: bin, dtype: int64
```

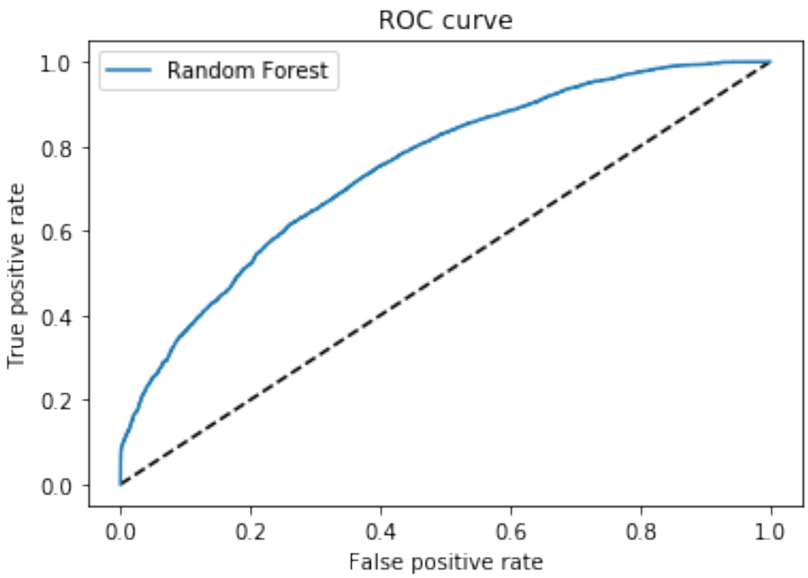
In [22]:

```
# At this stage you may wish to run Grid search CV, but I'm skipping that.

n_estimators, max_depth, c_random_state = 500, 7, 42

# Random Forest Model
rf = RandomForestClassifier(max_depth=max_depth,
                            n_estimators=n_estimators,
                            criterion='entropy',
                            class_weight = None, #This will be cover in next
                            random_state=c_random_state)

X = secondary_dollar.reindex(m_label0.index) # this dataframe only contain a
y = m_label0['bin']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shu

rf.fit(X_train, y_train.values.ravel())
```

Out[22]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entrop
y',
                       max_depth=7, max_features='auto', max_leaf_nodes=Non
e,
                       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=500,
                       n_jobs=None, oob_score=False, random_state=42, verbo
se=0,
                       warm_start=False)
```

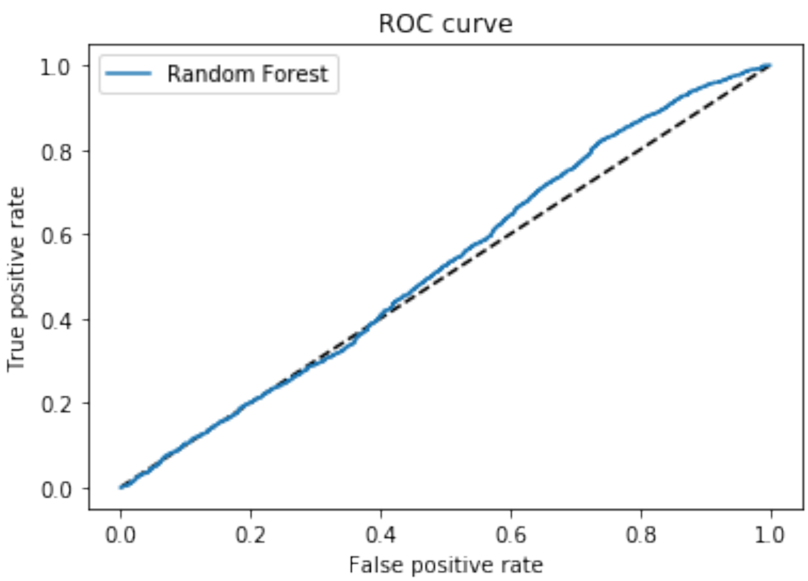
In [23]:
```
# Performance Metrics
y_prob = rf.predict_proba(X_train)[:, 1] #here we are only interested in Tru
y_pred = rf.predict(X_train)

p('Matrix training report for primary model & secondary model\n')

rs.report_matrix(actual_data = y_train, # we need to use our train data from
                 prediction_data = y_pred,
                 ROC = y_prob)
```

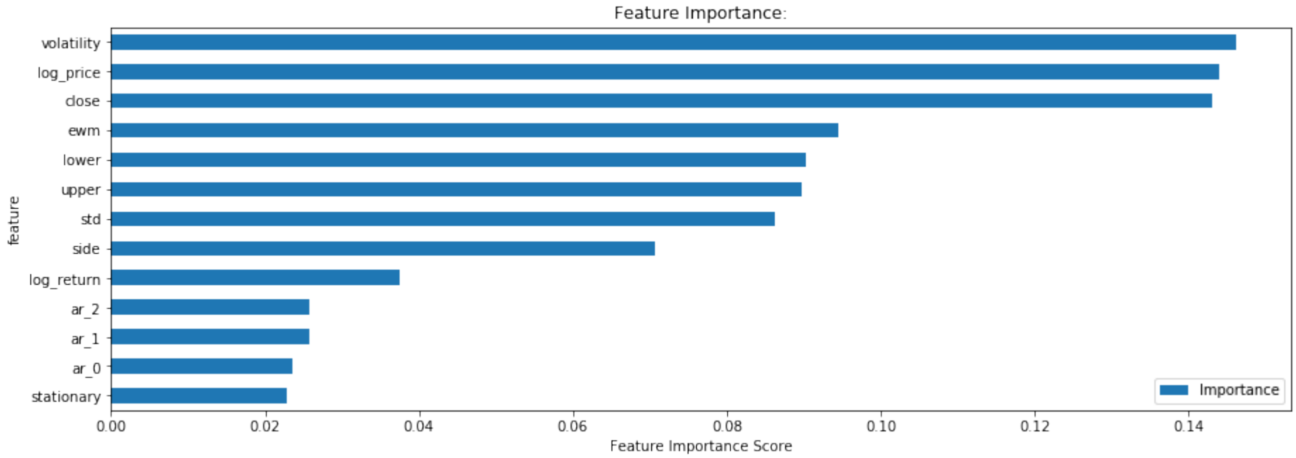
```
Matrix training report for primary model & secondary model

 Classification Report
=======================================================
              precision    recall  f1-score   support

         0.0       0.64      0.83      0.72      5721
         1.0       0.71      0.48      0.57      5059

    accuracy                           0.66     10780
   macro avg       0.67      0.65      0.65     10780
weighted avg       0.67      0.66      0.65     10780


 Confusion Matrix
=======================================================
[[TN, FP]
 [FN, TP]]

[[4733  988]
 [2655 2404]]

 Accuracy Score
=======================================================
0.6620593692022263
```



In [24]:
```
# Meta-label
# Performance Metrics
y_prob = rf.predict_proba(X_test)[:, 1] #here we are only interested in True
y_pred = rf.predict(X_test)

p('Matrix test report for primary model & secondary model\n')

rs.report_matrix(actual_data = y_test,
                 prediction_data = y_pred,
                 ROC = y_prob)

rs.feat_imp(rf, X)
```

```
Matrix test report for primary model & secondary model

 Classification Report
=======================================================
              precision    recall  f1-score   support

         0.0       0.54      0.37      0.43      2280
         1.0       0.53      0.69      0.60      2340

    accuracy                           0.53      4620
   macro avg       0.53      0.53      0.52      4620
weighted avg       0.53      0.53      0.52      4620


 Confusion Matrix
=======================================================
[[TN, FP]
 [FN, TP]]

[[ 833 1447]
 [ 720 1620]]

 Accuracy Score
=======================================================
0.530952380952381
```





In [ ]:
```
**Now we start to create only primary model**
```

In [25]:
```
events1 = rs.cs_filter(pri_dollar['close'],
                    limit = pri_dollar['volatility'].mean())

vb1 = rs.vert_barrier(data = pri_dollar['close'],
                 events = events1,
                 period = 'days',
                 freq = 1)

tb1 = rs.tri_barrier(data = pri_dollar['close'],
                events = events1,
                trgt = pri_dollar['volatility'],
                min_req = 0.002,
                num_threads = 3,
                ptSl = [0,2], #change ptSl into [0,2]
                t1 = vb1,
                side = None)

m_label1 = rs.meta_label(data = pri_dollar['close'],
                    events = tb1,
                    drop = 0.05) # take note we do not have a side hence w
```

```
C:\Users\Wei_X\Desktop\Python\research\Labels\triple_barrier_method.py:75: U
serWarning: Data and events index shape must be same, reindex data to fit ev
ents
  warnings.warn('Data and events index shape must be same, reindex data to f
it events')
C:\Users\Wei_X\Desktop\Python\research\Labels\triple_barrier_method.py:112:
UserWarning: Not Recommended: No side prediction provided
  warnings.warn('Not Recommended: No side prediction provided')
[                                              t1  sl  pt
2015-09-09 13:36:53.472 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:40:56.133 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:45:08.189 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:51:11.450 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 14:02:04.210 2015-09-10 14:05:19.003 NaT NaT
...                                           ...  ..  ..
2016-04-05 01:16:26.261 2016-04-06 02:45:07.823 NaT NaT
```

```
2016-04-05 06:02:04.305 2016-04-06 07:07:24.337 NaT NaT
2016-04-05 07:11:07.085 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 07:37:56.273 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 08:24:13.547 2016-04-06 09:05:34.702 NaT NaT

[5142 rows x 3 columns]] this out
[                                               t1  sl  pt
2015-09-09 13:36:53.472 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:40:56.133 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:45:08.189 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:51:11.450 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 14:02:04.210 2015-09-10 14:05:19.003 NaT NaT
...                                             ...  ..  ..
2016-04-05 01:16:26.261 2016-04-06 02:45:07.823 NaT NaT
2016-04-05 06:02:04.305 2016-04-06 07:07:24.337 NaT NaT
2016-04-05 07:11:07.085 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 07:37:56.273 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 08:24:13.547 2016-04-06 09:05:34.702 NaT NaT

[5142 rows x 3 columns],                                               t1  sl
pt
2015-01-05 14:54:26.286 2015-01-06 15:16:04.445 NaT NaT
2015-01-05 14:57:13.616 2015-01-06 15:16:04.445 NaT NaT
2015-01-05 15:01:57.494 2015-01-06 15:16:04.445 NaT NaT
2015-01-05 15:07:29.012 2015-01-06 15:16:04.445 NaT NaT
2015-01-05 15:13:09.655 2015-01-06 15:16:04.445 NaT NaT
...                                             ...  ..  ..
2015-09-09 08:33:28.634 2015-09-10 09:33:29.450 NaT NaT
2015-09-09 10:21:19.955 2015-09-10 11:43:14.539 NaT NaT
2015-09-09 12:02:05.852 2015-09-10 12:19:25.229 NaT NaT
2015-09-09 13:06:01.330 2015-09-10 13:30:20.359 NaT NaT
2015-09-09 13:31:24.524 2015-09-10 13:35:08.110 NaT NaT

[5142 rows x 3 columns]] this out
[                                               t1  sl  pt
2015-09-09 13:36:53.472 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:40:56.133 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:45:08.189 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 13:51:11.450 2015-09-10 13:59:08.553 NaT NaT
2015-09-09 14:02:04.210 2015-09-10 14:05:19.003 NaT NaT
...                                             ...  ..  ..
2016-04-05 01:16:26.261 2016-04-06 02:45:07.823 NaT NaT
2016-04-05 06:02:04.305 2016-04-06 07:07:24.337 NaT NaT
2016-04-05 07:11:07.085 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 07:37:56.273 2016-04-06 08:05:23.022 NaT NaT
2016-04-05 08:24:13.547 2016-04-06 09:05:34.702 NaT NaT

[5142 rows x 3 columns],                                               t1  sl
pt
2015-01-05 14:54:26.286 2015-01-06 15:16:04.445 NaT NaT
2015-01-05 14:57:13.616 2015-01-06 15:16:04.445 NaT NaT
2015-01-05 15:01:57.494 2015-01-06 15:16:04.445 NaT NaT
2015-01-05 15:07:29.012 2015-01-06 15:16:04.445 NaT NaT
```

```
2015-01-05 15:13:09.655 2015-01-06 15:16:04.445 NaT NaT
...                                         ...  ..  ..
2015-09-09 08:33:28.634 2015-09-10 09:33:29.450 NaT NaT
2015-09-09 10:21:19.955 2015-09-10 11:43:14.539 NaT NaT
2015-09-09 12:02:05.852 2015-09-10 12:19:25.229 NaT NaT
2015-09-09 13:06:01.330 2015-09-10 13:30:20.359 NaT NaT
2015-09-09 13:31:24.524 2015-09-10 13:35:08.110 NaT NaT

[5142 rows x 3 columns],                                                t1  sl
pt
2016-04-05 09:17:57.890 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 10:11:56.123 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 11:26:40.687 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 12:10:26.367 2016-04-06 13:14:38.661 NaT NaT
2016-04-05 12:55:36.469 2016-04-06 13:14:38.661 NaT NaT
...                                         ...  ..  ..
2016-12-30 20:22:33.456                     NaT NaT NaT
2016-12-30 20:32:57.188                     NaT NaT NaT
2016-12-30 20:44:21.481                     NaT NaT NaT
2016-12-30 20:50:57.567                     NaT NaT NaT
2016-12-30 20:55:33.160                     NaT NaT NaT

[5141 rows x 3 columns]]
```

```
2020-05-24 19:48:27.258258 33.33% _pt_sl_t1 done after 0.41 minutes. Remaini
ng 0.83 minutes.
2020-05-24 19:48:27.258258 66.67% _pt_sl_t1 done after 0.41 minutes. Remaini
ng 0.21 minutes.
```

```
 this out
```

```
2020-05-24 19:48:27.445715 100.0% _pt_sl_t1 done after 0.42 minutes. Remaini
ng 0.0 minutes.
```

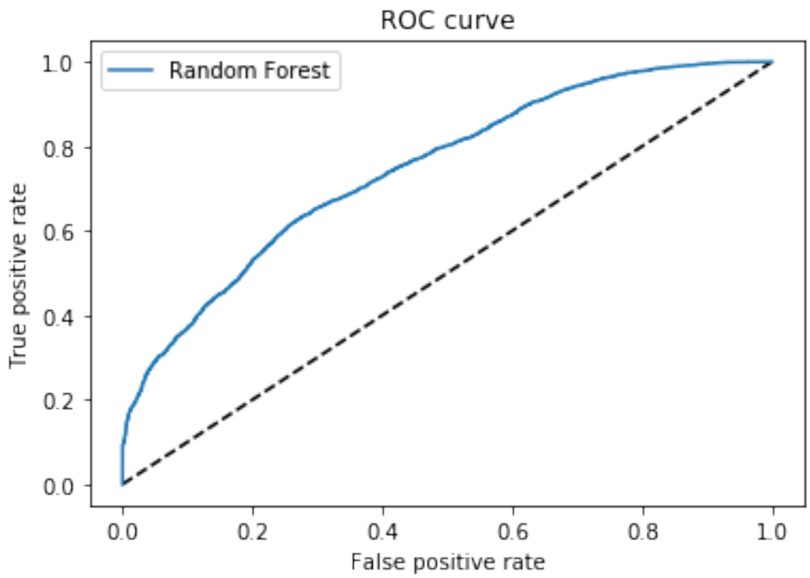
In [26]:

```
# Random Forest Model
rf = RandomForestClassifier(max_depth=max_depth,
                            n_estimators=n_estimators,
                            criterion='entropy',
                            class_weight = None, #This will be cover in next
                            random_state=c_random_state)

X = pri_dollar.reindex(m_label1.index) # this dataframe only contain all our
y = m_label1['bin']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shu

rf.fit(X_train, y_train.values.ravel())
```

Out[26]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entrop
y',
                       max_depth=7, max_features='auto', max_leaf_nodes=Non
e,
                       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=500,
                       n_jobs=None, oob_score=False, random_state=42, verbo
se=0,
                       warm_start=False)
```

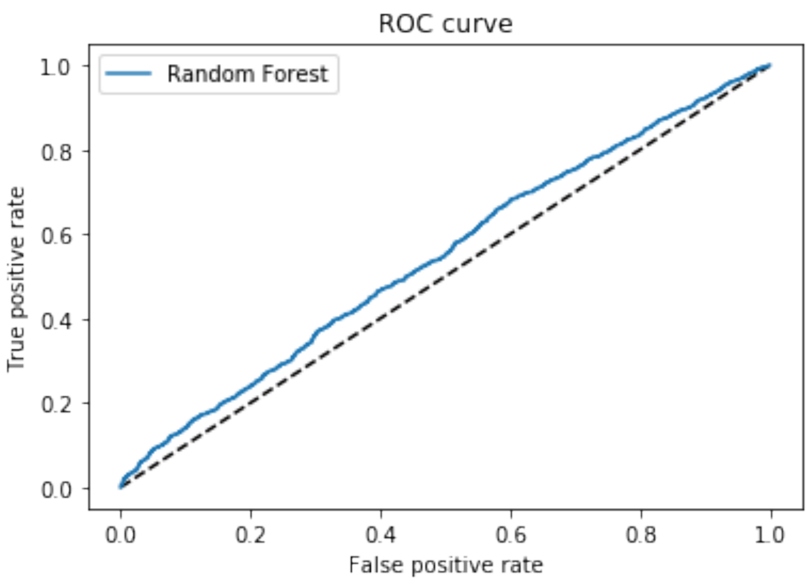
In [27]:
```python
# Performance Metrics
y_prob = rf.predict_proba(X_train)[:, 1] #here we are only interested in Tru
y_pred = rf.predict(X_train)

p('Matrix training report for primary model only\n')

rs.report_matrix(actual_data = y_train, # we need to use our train data from
                 prediction_data = y_pred,
                 ROC = y_prob)
```

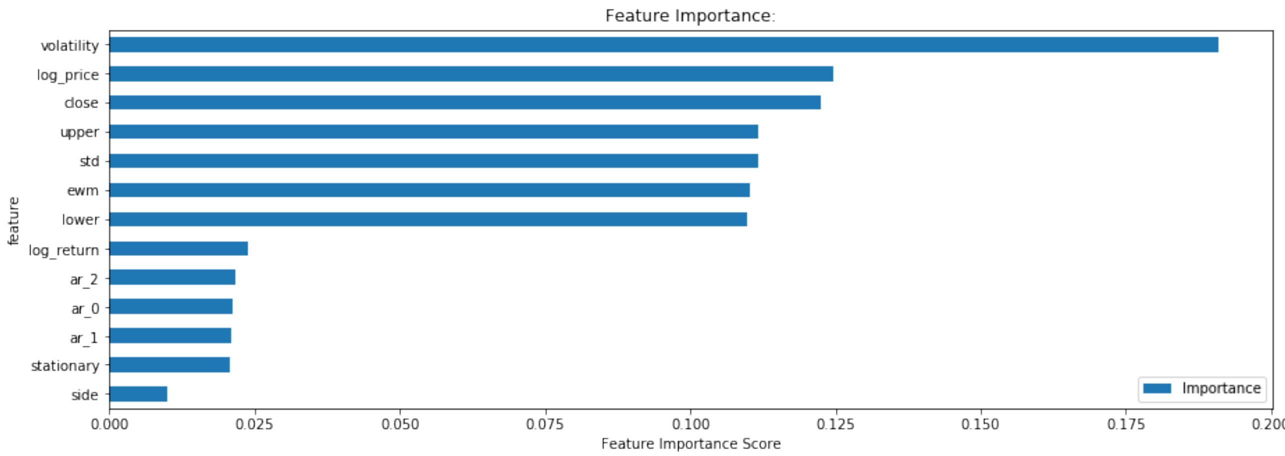
```
Matrix training report for primary model only

 Classification Report
=======================================================
              precision    recall  f1-score   support

        -1.0       0.71      0.43      0.54      4965
         1.0       0.63      0.85      0.73      5748

    accuracy                           0.66     10713
   macro avg       0.67      0.64      0.63     10713
weighted avg       0.67      0.66      0.64     10713


 Confusion Matrix
=======================================================
[[TN, FP]
 [FN, TP]]

[[2133 2832]
 [ 851 4897]]

 Accuracy Score
=======================================================
0.6562120787827873
```



In [28]:
```
# Meta-label
# Performance Metrics
y_prob = rf.predict_proba(X_test)[:, 1] #here we are only interested in True
y_pred = rf.predict(X_test)

p('Matrix test report for primary model only\n')

rs.report_matrix(actual_data = y_test,
                 prediction_data = y_pred,
                 ROC = y_prob)

rs.feat_imp(rf, X)
```

```
Matrix test report for primary model only

 Classification Report
=======================================================
              precision    recall  f1-score   support

        -1.0       0.46      0.73      0.56      2027
         1.0       0.60      0.31      0.41      2565

    accuracy                           0.50      4592
   macro avg       0.53      0.52      0.49      4592
weighted avg       0.54      0.50      0.48      4592


 Confusion Matrix
=======================================================
[[TN, FP]
 [FN, TP]]

[[1484  543]
 [1762  803]]

 Accuracy Score
=======================================================
0.4980400696864111
```





Based on our matrix report

The comparisons was made in ceteris paribus condition as much as possible.

All comparison will be made based on test data only, train data will be excluded.

Accuracy comparison

Accuracy is sum of True Positive and True Negative divided by overall set of items

There is an improvement in accuracy rate when meta-label (Primary & secondary model score yield 0.53), with original yielding only 0.48.

Accuracy +0.05 improvement (10% increase) from the original, +0.0342 improvement (6.8% increase) from primary model only.

However, in order to correctly use this method. Dr Marco Lopez De Prado did mentioned the below:

> "First, we build a model that achieve high recall, even if precision is not particularly high.
>
> Second correct for low precision by applying meta-label to the positives predicted by the primary model."
>
> Advances in Financial Machine Learning, page 52

However, for primary model only case. (-1,1) are consider price actions label, which in my opinion does not seem to work well with ML. But it does improve accuracy score by a small margin against original data with no labels.

In our case, we filtered out labels that touched vertical barrier first from primary model only.

F1 scores comparison

Measures the efficiency of classifer (Harmonic mean of both precision and recall)

Using both primary and secondary models to identify True Positive yields a score of 0.6 (for both long and short).

while using primary model only which gives 0.56 (for short) and 0.4 (for long).

F1 score +0.04 (7% increase/ short) and +0.2 (50% increase/ long) improvement, when compared against primary model only.

> "Meta-labeling is particularly helpful when you want to achieve higher F1-scores."
>
> Advances in Financial Machine Learning, page 52

Other observations

Stationarity absolute return series as a optional key feature, does not seem relevant at all since the ML does not recognize it after log price absolute change. Hence it is lowly ranked in feature importance graph.

For secondary model

Crossing averages and volatility does seem to be at the top of the key features importance. This seems to say, ML model recognize that as key feature for predictions, while auto-correlation does not seem that important.

The ML model did realised, we were using those indicators as our primary models.

For Primary model

The ML model only recognize we were using volatility as our benchmark (tri_barrier func cs_filter as trgt), when we did not use any (0,1) meta-labels.

Conclusion

To get a higher F1 score and better accuracy, quants should use both primary (To let it decide bet direction) while using a secondary model to decide bet size (To bet or not).

Stationarity is an important concept, especially to mean-reversion strategy. As Stationary series act as an anchor which the strategy will revert to eventually.

We will cover more with other examples regarding stationarity in the next chapter.