ABU 量化系统 简介(版本 0.1)

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第八部分 解决方案B

'非均衡胜负收益'带来的必然'非均衡胜负比例',目标由'因子'的能力解决一部分,'模式识别'提升关键的一部分

python import ZEnv import ZLog import ZCommonUtil %matplotlib inline

python from UmpMain import UmpMainClass from UmpJump import UmpJumpClass
from MlFiterJumpPd import MlFiterJumpPdClass

python fn = './data/cache/golden_n6_test_abu' key = 'golden_n6_test_abu'
orders_pd_test = ZCommonUtil.load_hdf5(fn, key) orders_pd_test.shape

(4837, 31)

python fn = './data/cache/golden_n6_train_abu' key = 'golden_n6_train_abu'
orders_pd_train = ZCommonUtil.load_hdf5(fn, key) orders_pd_train.shape

(42538, 31)

使用全量测试集数据

python fn = './data/cache/orders_pd_ump_hit_predict_abu' key =
'orders_pd_ump_hit_predict_abu' orders_pd_ump = ZCommonUtil.load_hdf5(fn,
key) orders_pd_ump.shape

(47374, 39)

jump ump 辅助裁决

python ump_jump = UmpJumpClass(orders_pd_ump, MlFiterJumpPdClass,

dd_threshold=21)

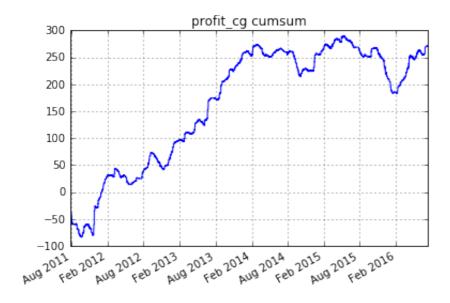
python ZLog.info(ump_jump.fiter.df.shape) ump_jump.fiter.df.head()

(5035, 3)

	result	jump_power	diff_days
2015-07-28	1	-1.382554	6
2015-07-28	0	-1.084962	21
2015-07-28	0	-3.415892	5
2015-07-28	0	-3.236708	4
2015-07-28	0	-1.307611	13

python ump_jump.show_general()

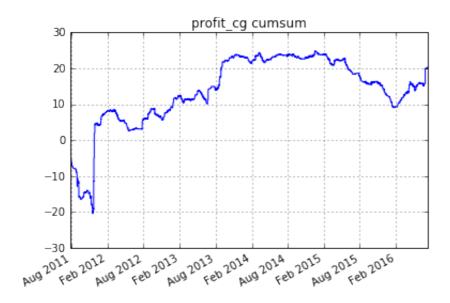
```
all fit order = (44906, 39)
win rate = 0.500757137131
profit_cg.sum() = 272.117613217
win mean = 0.0743788075658 loss_mean = -0.0626291433739
```



跳空监控区,收益小于整个区间

python ump_jump.show_general(use_fiter=True)

```
all fit order = (5035, 39)
win rate = 0.498907646475
profit_cg.sum() = 20.2331512267
win mean = 0.0673137719871 loss_mean = -0.0591414557032
```



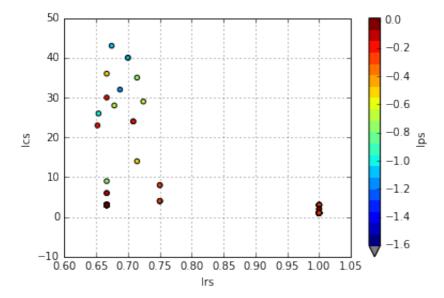
make a joke

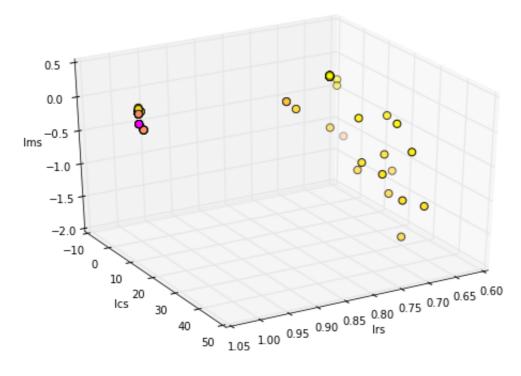
python ump_jump.fiter().estimator.svc()
ump_jump.fiter().train_test_split_xy()

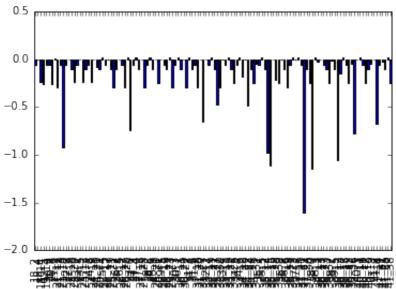
```
(5035, 2)
(4531, 2)
(504, 2)
accuracy = 0.56
precision_score = 0.57
recall_score = 0.54
                      recall f1-score
            precision
                                         support
                          0.59
      loss
                0.55
                                   0.57
                                             247
       win
                0.57
                          0.54
                                   0.56
                                             257
avg / total
                0.56
                          0.56
                                   0.56
                                             504
Confusion Matrix [[145 102]
 [119 138]]
         Predicted
        | 0 | 1 |
        |----|
      0 | 145 | 102 |
       |----|
Actual
      1 | 119 | 138 |
        |----|
```

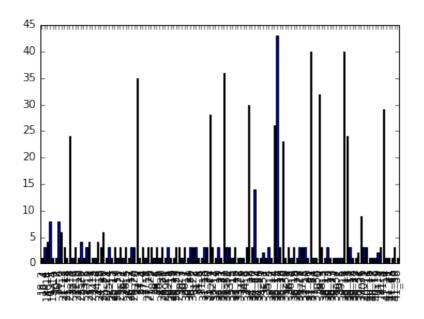
p_ncs的选择要依据数据集的大小

python import numpy as np
ump_jump.gmm_component_filter(p_ncs=np.arange(18, 42), threshold=0.65)









	lcs	Irs	lps	lms
18_2	1.0	1.000000	-0.059441	-0.059441
18_4	3.0	0.666667	-0.003412	-0.001137
18_14	4.0	0.750000	-0.233595	-0.058399
19_5	8.0	0.750000	-0.265865	-0.033233
19_14	1.0	1.000000	-0.059441	-0.059441
20_2	1.0	1.000000	-0.059441	-0.059441
20_8	8.0	0.750000	-0.265865	-0.033233
21_2	6.0	0.666667	0.011840	0.001973
21_12	3.0	1.000000	-0.294978	-0.098326
21_13	1.0	1.000000	-0.059441	-0.059441
21_18	24.0	0.708333	-0.921051	-0.038377
22_2	1.0	1.000000	-0.059441	-0.059441
22_9	3.0	0.666667	-0.003412	-0.001137
22_10	1.0	1.000000	-0.101029	-0.101029
22_20	4.0	0.750000	-0.233595	-0.058399
23_2	1.0	1.000000	-0.059441	-0.059441
23_5	3.0	0.666667	-0.003412	-0.001137

23_12	4.0	0.750000	-0.233595	-0.058399
23_13	1.0	1.000000	-0.101029	-0.101029
24_3	1.0	1.000000	-0.059441	-0.059441
24_6	4.0	0.750000	-0.233595	-0.058399
24_18	3.0	0.666667	-0.003412	-0.001137
24_20	6.0	0.666667	-0.077712	-0.012952
24_21	1.0	1.000000	-0.101029	-0.101029
25_4	3.0	0.666667	0.015253	0.005084
25_15	1.0	1.000000	-0.059441	-0.059441
25_17	3.0	0.666667	-0.003412	-0.001137
25_19	1.0	1.000000	-0.101029	-0.101029
25_21	3.0	1.000000	-0.294978	-0.098326
26_2	1.0	1.000000	-0.101029	-0.101029
37_36	1.0	1.000000	-0.248848	-0.248848
38_0	32.0	0.687500	-1.140307	-0.035635
38_3	3.0	0.666667	0.015253	0.005084
38_12	1.0	1.000000	-0.028857	-0.028857
38_13	3.0	0.666667	-0.003412	-0.001137
38_17	1.0	1.000000	-0.059441	-0.059441
38_23	1.0	1.000000	-0.101029	-0.101029
38_37	1.0	1.000000	-0.248848	-0.248848
39_2	1.0	1.000000	-0.009235	-0.009235
39_5	1.0	1.000000	-0.101029	-0.101029
39_12	40.0	0.700000	-1.052118	-0.026303
39_13	24.0	0.708333	-0.150335	-0.006264
39_17	3.0	0.666667	0.015253	0.005084
39_18	1.0	1.000000	-0.059441	-0.059441

39_22	1.0	1.000000	-0.248848	-0.248848
39_32	2.0	1.000000	-0.046130	-0.023065
39_36	9.0	0.666667	-0.780621	-0.086736
40_3	3.0	0.666667	-0.003412	-0.001137
40_11	3.0	0.666667	0.015253	0.005084
40_16	1.0	1.000000	-0.059441	-0.059441
40_17	1.0	1.000000	-0.248848	-0.248848
40_18	1.0	1.000000	-0.101029	-0.101029
40_19	2.0	1.000000	-0.046130	-0.023065
41_3	3.0	0.666667	-0.003412	-0.001137
41_8	29.0	0.724138	-0.679913	-0.023445
41_14	1.0	1.000000	-0.059441	-0.059441
41_21	1.0	1.000000	-0.028857	-0.028857
41_25	1.0	1.000000	-0.101029	-0.101029
41_30	3.0	0.666667	0.015253	0.005084
41_38	1.0	1.000000	-0.248848	-0.248848

python ump_jump.nts['25_15']

	result	jump_power	diff_days	ind	ss	profit
2014-01-27	0	-85.133358	14	2062	15	-0.059441

跳空能量向下两倍以上,10天左右的认为不应买入

python ii = ump_jump.nts['39_12'] ii

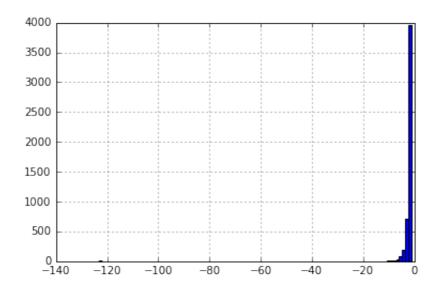
	result	jump_power	diff_days	ind	ss	profit
2015-08-10	0	-2.706233	11	41	12	-0.176608
2015-10-01	0	-2.702703	9	143	12	-0.053364
2015-10-23	1	-2.418221	10	170	12	0.062206
2015-11-16	1	-3.402683	11	249	12	0.113208

2015-11-17	0	-3.153450	10	262	12	-0.032323
2015-11-25	0	-3.251595	12	283	12	-0.128647
2016-01-04	0	-3.497082	10	354	12	-0.013350
2016-04-15	0	-2.571623	9	578	12	-0.007959
2016-05-16	0	-3.490188	10	672	12	-0.017408
2014-10-03	0	-2.728997	10	1016	12	-0.003032
2014-10-08	1	-3.083089	12	1020	12	0.049996
2014-12-05	1	-2.483176	10	1122	12	0.060298
2014-12-30	0	-2.631553	10	1193	12	-0.027207
2015-05-19	0	-2.951475	11	1493	12	-0.044630
2015-06-18	0	-2.629061	9	1580	12	-0.026883
2013-08-27	1	-3.107009	12	1762	12	0.096847
2013-12-02	1	-2.795049	10	1960	12	0.031864
2013-12-11	0	-2.657454	11	1989	12	-0.017341
2014-03-12	0	-3.151759	12	2141	12	-0.030650
2014-05-14	0	-3.117394	11	2277	12	-0.000439
2014-06-23	1	-2.646682	11	2336	12	0.040926
2012-08-24	1	-3.501264	10	2500	12	0.025974
2012-09-20	0	-2.593575	9	2575	12	-0.010300
2012-10-22	0	-2.853089	10	2690	12	-0.010843
2012-12-03	0	-2.946918	11	2829	12	-0.134032
2013-03-14	0	-2.873770	9	3152	12	-0.080194
2013-03-22	0	-2.482930	10	3169	12	-0.026621
2013-05-23	0	-2.795248	9	3342	12	-0.046241
2011-08-30	0	-3.409071	11	3633	12	-0.086524
2011-09-16	0	-2.776829	9	3785	12	-0.172645
2011-10-07	0	-2.599565	9	3838	12	-0.160468
2011-10-28	0	-2.456538	10	3871	12	-0.067081

2011-11-14	1	-3.023274	10	3972	12	0.023094
2011-11-14	0	-2.891566	10	3973	12	-0.095696
2011-11-14	0	-3.050215	10	3974	12	-0.037638
2011-11-22	1	-3.099930	12	4243	12	0.035945
2011-12-23	1	-2.819676	10	4509	12	0.016492
2012-04-02	0	-2.681171	9	4859	12	-0.124722
2012-04-10	1	-2.707060	11	4872	12	0.034586
2012-05-16	0	-3.198386	11	4962	12	-0.010707

python import scipy.stats as scs import MlFiterBinsCs
ZLog.info(scs.normaltest(ump_jump.fiter.df.jump_power))
MlFiterBinsCs.show_orders_hist(ump_jump.fiter.df, s_list = ['jump_power'])

NormaltestResult(statistic=11612.386867948926, pvalue=0.0)



```
jump_power show hist and qcuts
(-1.0692, -1.000217]
(-1.243, -1.149]
                        504
(-1.669, -1.499]
                        504
(-2.304, -1.932]
                        504
[-123.0916, -3.0491]
                        504
(-1.149, -1.0692]
                        503
(-1.366, -1.243]
                        503
(-1.499, -1.366]
                        503
(-1.932, -1.669]
                        503
(-3.0491, -2.304]
                        503
Name: jump_power, dtype: int64
```

jump power选取IIps没有执行最优化求解,因为数据量不够,按照0, 0, 0.65来办

```
python llps = ump_jump.cprs[(ump_jump.cprs['lps'] <= 0) &
(ump_jump.cprs['lms'] <= 0 ) & (ump_jump.cprs['lrs'] >= 0.65) & (
(ump_jump.cprs['lcs'] >= 20) | (ump_jump.cprs['lrs'] == 1) )] llps
```

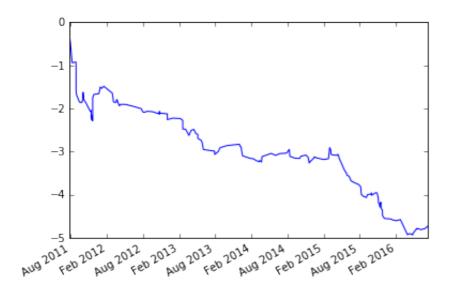
	lcs	Irs	lps	lms
18_2	1.0	1.000000	-0.059441	-0.059441
19_14	1.0	1.000000	-0.059441	-0.059441
20_2	1.0	1.000000	-0.059441	-0.059441
21_12	3.0	1.000000	-0.294978	-0.098326
21_13	1.0	1.000000	-0.059441	-0.059441
21_18	24.0	0.708333	-0.921051	-0.038377
22_2	1.0	1.000000	-0.059441	-0.059441
22_10	1.0	1.000000	-0.101029	-0.101029
23_2	1.0	1.000000	-0.059441	-0.059441
23_13	1.0	1.000000	-0.101029	-0.101029
24_3	1.0	1.000000	-0.059441	-0.059441
24_21	1.0	1.000000	-0.101029	-0.101029
25_15	1.0	1.000000	-0.059441	-0.059441
25_19	1.0	1.000000	-0.101029	-0.101029
25_21	3.0	1.000000	-0.294978	-0.098326
26_2	1.0	1.000000	-0.101029	-0.101029

27_0 3. 27_3 1. 27_9 1. 27_23 3. 28_2 1. 28_9 1.	5.0 .0 .0 .0 .0	1.000000 0.714286 1.000000 1.000000 1.000000 1.000000 1.000000	-0.294978 -0.745038 -0.059441 -0.101029 -0.294978 -0.059441 -0.101029 -0.248848	-0.098326 -0.021287 -0.059441 -0.101029 -0.098326 -0.059441 -0.101029
27_3 1. 27_9 1. 27_23 3. 28_2 1. 28_9 1.	.0 .0 .0 .0 .0	1.000000 1.000000 1.000000 1.000000	-0.059441 -0.101029 -0.294978 -0.059441 -0.101029	-0.059441 -0.101029 -0.098326 -0.059441 -0.101029
27_9 1. 27_23 3. 28_2 1. 28_9 1.	.0 .0 .0 .0	1.000000 1.000000 1.000000 1.000000	-0.101029 -0.294978 -0.059441 -0.101029	-0.101029 -0.098326 -0.059441 -0.101029
27_23 3 28_2 1 28_9 1	.0 .0 .0	1.000000 1.000000 1.000000	-0.294978 -0.059441 -0.101029	-0.098326 -0.059441 -0.101029
28_2 1. 28_9 1.	.0	1.000000	-0.059441 -0.101029	-0.059441 -0.101029
28_9 1	.0	1.000000	-0.101029	-0.101029
	.0			
28_21 1		1.000000	-0.248848	
	.0			-0.248848
29_15 1.		1.000000	-0.059441	-0.059441
29_19 1.	.0	1.000000	-0.101029	-0.101029
29_27 3	.0	1.000000	-0.294978	-0.098326
30_3 1.	.0	1.000000	-0.059441	-0.059441
30_11 1.	.0	1.000000	-0.101029	-0.101029
35_28 23	3.0	0.652174	-0.215931	-0.009388
35_30 1.	.0	1.000000	-0.248848	-0.248848
36_8 1.	.0	1.000000	-0.101029	-0.101029
36_16 3.	.0	1.000000	-0.294978	-0.098326
36_18 1.	.0	1.000000	-0.059441	-0.059441
37_20 1.	.0	1.000000	-0.059441	-0.059441
37_21 4	0.0	0.700000	-1.602485	-0.040062
37_24 1.	.0	1.000000	-0.101029	-0.101029
37_36 1.	.0	1.000000	-0.248848	-0.248848
38_0 3	2.0	0.687500	-1.140307	-0.035635
38_12 1.	.0	1.000000	-0.028857	-0.028857
38_17 1.	.0	1.000000	-0.059441	-0.059441
38_23 1.	.0	1.000000	-0.101029	-0.101029

38_37	1.0	1.000000	-0.248848	-0.248848
39_2	1.0	1.000000	-0.009235	-0.009235
39_5	1.0	1.000000	-0.101029	-0.101029
39_12	40.0	0.700000	-1.052118	-0.026303
39_13	24.0	0.708333	-0.150335	-0.006264
39_18	1.0	1.000000	-0.059441	-0.059441
39_22	1.0	1.000000	-0.248848	-0.248848
39_32	2.0	1.000000	-0.046130	-0.023065
40_16	1.0	1.000000	-0.059441	-0.059441
40_17	1.0	1.000000	-0.248848	-0.248848
40_18	1.0	1.000000	-0.101029	-0.101029
40_19	2.0	1.000000	-0.046130	-0.023065
41_8	29.0	0.724138	-0.679913	-0.023445
41_14	1.0	1.000000	-0.059441	-0.059441
41_21	1.0	1.000000	-0.028857	-0.028857
41_25	1.0	1.000000	-0.101029	-0.101029
41_38	1.0	1.000000	-0.248848	-0.248848

python ump_jump.choose_cprs_component(llps)

```
nts_pd.shape = (182, 6)
nts_pd loss rate = 0.681318681319
improved rate = 0.0131082423039
predict win rate = 0.512015888779
```

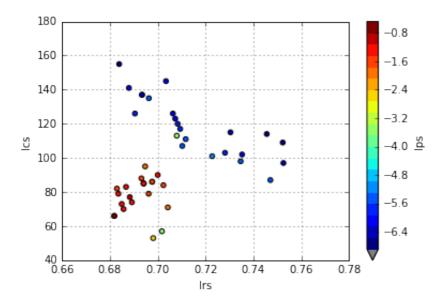


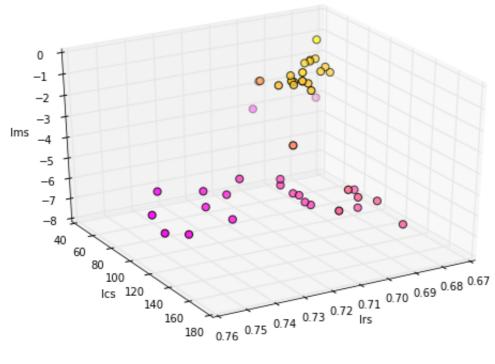
python ump_jump.dump_clf(llps)

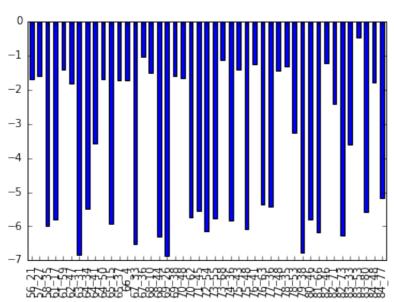
python from MlFiterDegPd import MlFiterDegPdClass

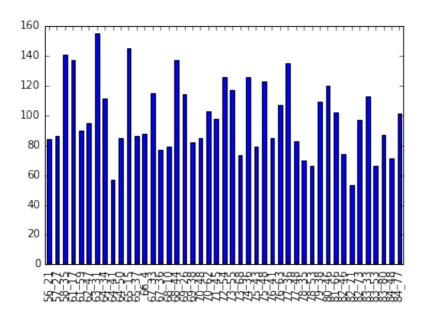
deg ump 主裁,只使用全局最优llps

python ump_deg = UmpMainClass(orders_pd_ump, MlFiterDegPdClass)
ump_deg.gmm_component_filter(p_ncs=np.arange(18, 85), threshold=0.68)







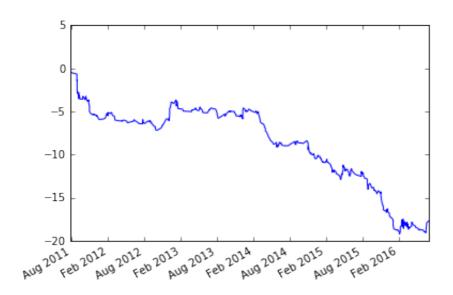


	lcs	Irs	lps	lms
56_21	84.0	0.702381	-1.699820	-0.020236
57_27	86.0	0.697674	-1.591000	-0.018500
58_35	141.0	0.687943	-5.994469	-0.042514
61_17	137.0	0.693431	-5.788397	-0.042251
61_59	90.0	0.700000	-1.401181	-0.015569
62_47	95.0	0.694737	-1.830953	-0.019273
63_31	155.0	0.683871	-6.826563	-0.044042
64_34	111.0	0.711712	-5.487420	-0.049436
64_41	57.0	0.701754	-3.558004	-0.062421
64_50	85.0	0.694118	-1.677678	-0.019737
65_15	145.0	0.703448	-5.934523	-0.040928
65_37	86.0	0.697674	-1.734857	-0.020173
66_4	88.0	0.693182	-1.715398	-0.019493
67_33	115.0	0.730435	-6.528349	-0.056768
67_36	77.0	0.688312	-1.016318	-0.013199
68_10	79.0	0.696203	-1.512461	-0.019145
68_44	137.0	0.693431	-6.297579	-0.045968

69_26	114.0	0.745614	-6.872898	-0.060289
69_38	82.0	0.682927	-1.584954	-0.019329
70_48	85.0	0.694118	-1.657861	-0.019504
70_62	103.0	0.728155	-5.746673	-0.055793
71_45	98.0	0.734694	-5.554473	-0.056678
72_54	126.0	0.706349	-6.144978	-0.048770
73_55	117.0	0.709402	-5.770077	-0.049317
73_68	73.0	0.684932	-1.130658	-0.015488
74_36	126.0	0.690476	-5.826468	-0.046242
75_43	79.0	0.683544	-1.393574	-0.017640
75_48	123.0	0.707317	-6.067599	-0.049330
76_41	85.0	0.694118	-1.257220	-0.014791
76_63	107.0	0.710280	-5.348693	-0.049988
77_36	135.0	0.696296	-5.407719	-0.040057
77_48	83.0	0.686747	-1.429252	-0.017220
78_35	70.0	0.685714	-1.308801	-0.018697
78_53	66.0	0.681818	-3.242988	-0.049136
79_38	109.0	0.752294	-6.785169	-0.062249
80_46	120.0	0.708333	-5.798165	-0.048318
81_66	102.0	0.735294	-6.190534	-0.060692
82_46	74.0	0.689189	-1.214181	-0.016408
82_71	53.0	0.698113	-2.419266	-0.045647
82_73	97.0	0.752577	-6.261241	-0.064549
83_33	113.0	0.707965	-3.611449	-0.031960
83_53	66.0	0.681818	-0.477639	-0.007237
83_80	87.0	0.747126	-5.564710	-0.063962
84_48	71.0	0.704225	-1.782087	-0.025100
84_77	101.0	0.722772	-5.183489	-0.051322

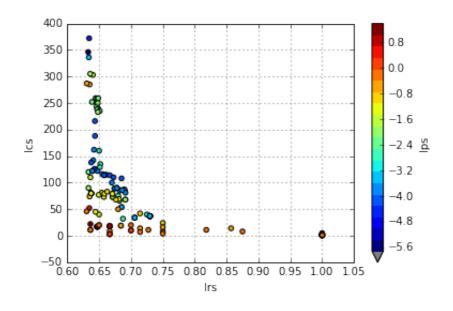
```
python brust_min = ump_deg.brust_min() llps =
ump_deg.cprs[(ump_deg.cprs['lps'] <= brust_min[0]) & (ump_deg.cprs['lms']
<= brust_min[1] ) & (ump_deg.cprs['lrs'] >= brust_min[2])]
ump_deg.choose_cprs_component(llps) ump_deg.dump_clf(llps)
```

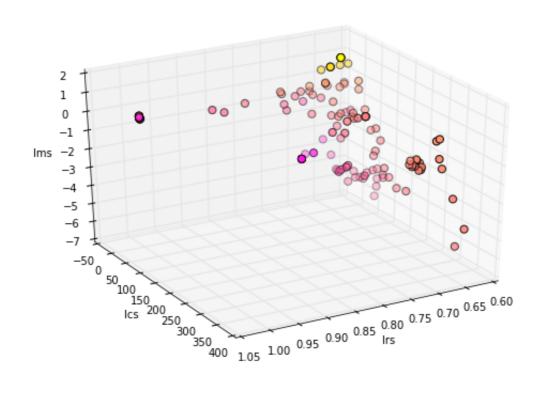
```
nts_pd.shape = (513, 7)
nts_pd loss rate = 0.690058479532
improved rate = 0.00434240413308
predict win rate = 0.505099541264
```

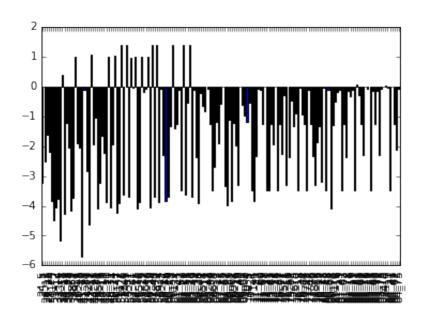


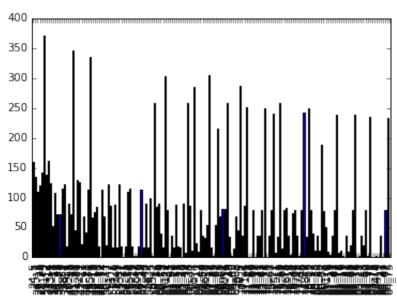
wave ump第二主裁

python from MlFiterWavePd import MlFiterWavePdClass ump_wave =
UmpMainClass(orders_pd_ump, MlFiterWavePdClass)
ump_wave.gmm_component_filter(p_ncs=np.arange(18, 85), threshold=0.63)









	lcs	Irs	lps	lms
24_5	160.0	0.650000	-3.223928	-0.020150
25_7	135.0	0.651852	-2.515814	-0.018636
26_15	110.0	0.636364	-1.624467	-0.014768
27_26	120.0	0.633333	-2.197939	-0.018316
28_24	142.0	0.640845	-3.833662	-0.026998
31_5	372.0	0.634409	-4.477736	-0.012037
31_12	138.0	0.637681	-4.040783	-0.029281

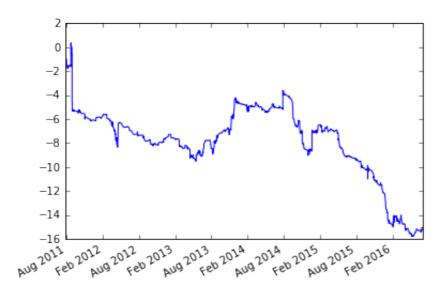
32_14	162.0	0.641975	-3.757361	-0.023194
33_5	124.0	0.645161	-5.155671	-0.041578
33_18	52.0	0.634615	0.401146	0.007714
34_11	108.0	0.685185	-4.270846	-0.039545
35_23	73.0	0.657534	-1.210312	-0.016580
36_28	73.0	0.671233	-2.032845	-0.027847
37_25	115.0	0.660870	-4.175807	-0.036311
38_7	122.0	0.647541	-3.728374	-0.030560
38_21	18.0	0.666667	1.009932	0.056107
39_9	90.0	0.633333	-1.914981	-0.021278
40_25	73.0	0.671233	-2.032845	-0.027847
41_10	346.0	0.632948	-5.712077	-0.016509
41_23	46.0	0.630435	-0.125099	-0.002720
41_31	129.0	0.651163	-2.841463	-0.022027
42_9	126.0	0.642857	-4.609681	-0.036585
42_22	22.0	0.636364	1.070885	0.048677
43_11	68.0	0.691176	-1.932722	-0.028422
44_28	42.0	0.714286	-1.051805	-0.025043
44_31	114.0	0.666667	-4.074704	-0.035743
45_6	336.0	0.633929	-3.224770	-0.009598
45_13	66.0	0.681818	-1.651001	-0.025015
46_10	75.0	0.680000	-2.241460	-0.029886
47_11	84.0	0.690476	-3.868414	-0.046053
•••				
81_0	50.0	0.680000	-0.499477	-0.009990
81_16	10.0	0.700000	-0.190936	-0.019094
81_19	5.0	1.000000	-0.117092	-0.023418
81_21	37.0	0.729730	-3.473791	-0.093886

81_62	80.0	0.637500	-1.248253	-0.015603
81_72	239.0	0.648536	-2.384517	-0.009977
81_78	7.0	0.714286	-0.162419	-0.023203
82_16	11.0	0.727273	-0.310766	-0.028251
82_19	3.0	1.000000	-0.095641	-0.031880
82_21	37.0	0.729730	-3.473791	-0.093886
82_31	10.0	0.700000	0.076625	0.007663
82_58	20.0	0.700000	-0.292118	-0.014606
82_62	80.0	0.637500	-1.248253	-0.015603
82_72	238.0	0.647059	-2.299922	-0.009664
82_78	1.0	1.000000	-0.015716	-0.015716
83_19	2.0	1.000000	-0.069436	-0.034718
83_21	37.0	0.729730	-3.473791	-0.093886
83_58	20.0	0.650000	-0.132397	-0.006620
83_62	80.0	0.637500	-1.248253	-0.015603
83_70	3.0	1.000000	-0.135101	-0.045034
83_72	235.0	0.651064	-2.291549	-0.009751
83_75	1.0	1.000000	-0.086957	-0.086957
83_78	1.0	1.000000	-0.015716	-0.015716
84_4	3.0	0.666667	0.029706	0.009902
84_19	1.0	1.000000	-0.042480	-0.042480
84_21	37.0	0.729730	-3.473791	-0.093886
84_31	1.0	1.000000	-0.004204	-0.004204
84_62	80.0	0.637500	-1.248253	-0.015603
84_72	233.0	0.648069	-2.120741	-0.009102
84_75	1.0	1.000000	-0.086957	-0.086957

python brust_min = ump_wave.brust_min() llps =

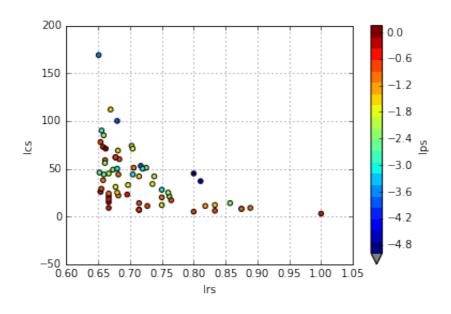
```
ump_wave.cprs[(ump_wave.cprs['lps'] <= brust_min[0]) &
(ump_wave.cprs['lms'] <= brust_min[1] ) & (ump_wave.cprs['lrs'] >=
brust_min[2])] ump_wave.choose_cprs_component(llps)
ump_wave.dump_clf(llps)
```

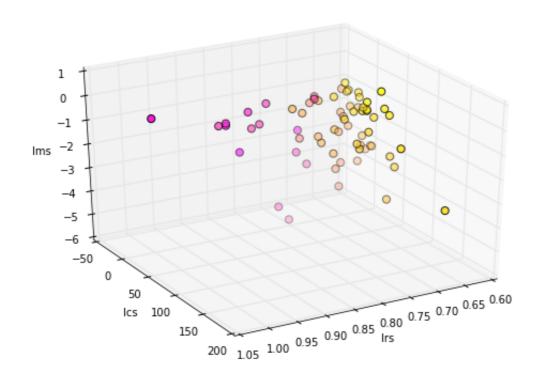
```
nts_pd.shape = (1126, 7)
nts_pd loss rate = 0.639431616341
improved rate = 0.00699238409121
predict win rate = 0.507749521222
```

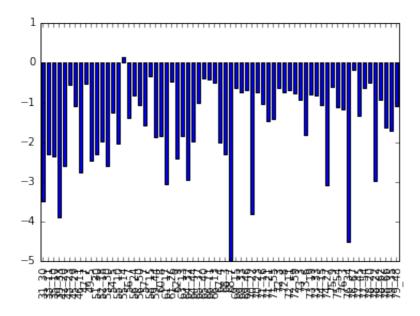


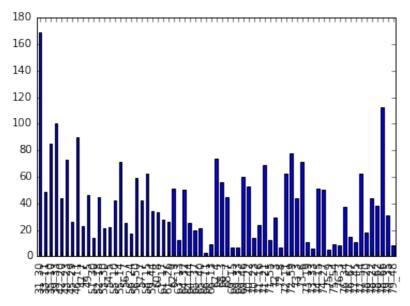
第三主裁

python from MlFiterMainPd import MlFiterMainPdClass ump_main =
UmpMainClass(orders_pd_ump, MlFiterMainPdClass)
ump_main.gmm_component_filter(p_ncs=np.arange(18, 80), threshold=0.65)









	lcs	Irs	lps	lms
31_30	169.0	0.650888	-3.488626	-0.020643
33_11	49.0	0.673469	-2.314873	-0.047242
35_10	85.0	0.658824	-2.364326	-0.027816
39_33	100.0	0.680000	-3.877226	-0.038772
42_20	44.0	0.659091	-2.604120	-0.059185
43_23	73.0	0.657534	-0.548995	-0.007520
45_29	26.0	0.653846	-1.105545	-0.042521

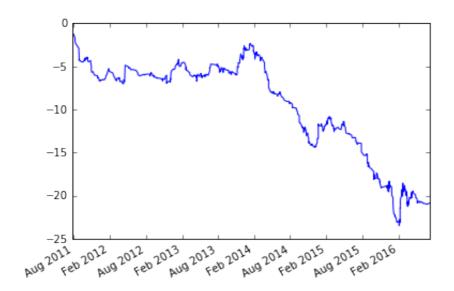
46_11	90.0	0.655556	-2.752587	-0.030584
47_7	23.0	0.695652	-0.536203	-0.023313
49_5	46.0	0.652174	-2.461245	-0.053505
51_30	14.0	0.857143	-2.291159	-0.163654
52_18	45.0	0.666667	-1.992503	-0.044278
53_30	21.0	0.761905	-2.606842	-0.124135
54_5	22.0	0.681818	-1.242849	-0.056493
55_10	42.0	0.738095	-2.028529	-0.048298
55_14	71.0	0.661972	0.153408	0.002161
56_7	25.0	0.680000	-1.394074	-0.055763
56_24	17.0	0.764706	-0.833099	-0.049006
56_50	59.0	0.661017	-1.069024	-0.018119
57_7	42.0	0.714286	-1.574196	-0.037481
58_15	62.0	0.677419	-0.331972	-0.005354
59_44	34.0	0.735294	-1.886792	-0.055494
60_8	33.0	0.696970	-1.858589	-0.056321
61_17	28.0	0.750000	-3.059575	-0.109271
61_26	26.0	0.653846	-0.486007	-0.018693
62_9	51.0	0.725490	-2.412638	-0.047307
63_13	12.0	0.750000	-1.847714	-0.153976
64_32	50.0	0.680000	-2.936657	-0.058733
64_44	25.0	0.760000	-1.977574	-0.079103
65_37	20.0	0.750000	-1.026872	-0.051344
•••				
69_33	7.0	0.714286	-0.757312	-0.108187
69_46	60.0	0.683333	-0.692344	-0.011539
70_22	53.0	0.716981	-3.815061	-0.071982
70_23	14.0	0.714286	-0.735310	-0.052522

71_16	24.0	0.666667	-1.032935	-0.043039
71_21	69.0	0.681159	-1.465262	-0.021236
71_55	12.0	0.833333	-1.425944	-0.118829
72_3	29.0	0.655172	-0.642314	-0.022149
72_8	7.0	0.714286	-0.757312	-0.108187
72_11	62.0	0.677419	-0.690655	-0.011140
72_59	78.0	0.653846	-0.769406	-0.009864
73_3	44.0	0.681818	-0.936858	-0.021292
73_6	71.0	0.704225	-1.829152	-0.025763
73_19	11.0	0.727273	-0.811367	-0.073761
73_33	6.0	0.833333	-0.820737	-0.136790
74_15	51.0	0.705882	-1.070951	-0.020999
74_27	50.0	0.720000	-3.096087	-0.061922
75_9	5.0	0.800000	-0.617400	-0.123480
75_54	9.0	0.888889	-1.126203	-0.125134
76_3	8.0	0.875000	-1.182426	-0.147803
76_34	37.0	0.810811	-4.498345	-0.121577
76_67	15.0	0.666667	-0.173521	-0.011568
77_45	11.0	0.818182	-1.324581	-0.120416
77_54	62.0	0.677419	-0.645419	-0.010410
78_20	18.0	0.666667	-0.495147	-0.027508
78_22	44.0	0.704545	-2.978029	-0.067682
78_62	38.0	0.657895	-0.941355	-0.024773
78_66	112.0	0.669643	-1.630110	-0.014555
79_35	31.0	0.677419	-1.715791	-0.055348
79_48	8.0	0.875000	-1.089348	-0.136168

python brust_min = ump_main.brust_min() llps =

```
ump_main.cprs[(ump_main.cprs['lps'] <= brust_min[0]) &
(ump_main.cprs['lms'] <= brust_min[1]) & (ump_main.cprs['lrs'] >=
brust_min[2])] ump_main.choose_cprs_component(llps)
ump_main.dump_clf(llps)
```

```
nts_pd.shape = (804, 7)
nts_pd loss rate = 0.661691542289
improved rate = 0.00578987217744
predict win rate = 0.506547009308
```



"python
