Prediction on Poor Performance Students

April 15, 2018

1 Prediction on Poor Performance Students

1.1 Outline

- Part 0. Automation setup
- Part 1. Data preparation (create new aggregated features, subset the data by cutting out future data, convert categorical variable, split train and test data)
- Part 2. Model building (cross validation, parameter tuning)
- Part 3. Model evaluation (confusion matrix, KS statistics, cumulative gain chart)

2 Part 0. Automation setup

- Select the metric to predict, the time to predict, the number of days to predict forward (for withdrawal), and algorithm
- Click on "run all below", the predictive model will be run automatically :)

In [4219]:
```
# Metric need to be predicted
metric = 'Fail' #'Withdrawn','Fail'
# Cut-off day
cutoff_i = 120
# For withdrawal only: number of days to predict forward
window_width = 7
# Algorithm
algorithm = 'Random Forest' #'Neural Network', 'XGBoost'
```

3 Part 1. Data Preparation

3.1 1.1 Load package

In [4284]:
```
import numpy as np
import pandas as pd
from pandas import Series, DataFrame
import warnings
warnings.filterwarnings('ignore')
```

In [4285]:
```
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, Ada
from sklearn.model_selection import GridSearchCV
```

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.cross_validation import train_test_split
from xgboost import XGBClassifier
```

3.2 1.2 Read file

```
In [2185]: course_student_all = pd.read_csv("~/Google Drive/MSBA@UMN/OULAD/course_student_all.c

In [2186]: assessment_student_all = pd.read_csv("~/Google Drive/MSBA@UMN/OULAD/course_student_a

In [2187]: vle_student_all = pd.read_csv("~/Google Drive/MSBA@UMN/OULAD/course_student_vle_fina
```

3.3 1.3 Basic aggregation before joining

3.3.1 1) Course student table

```
In [4286]: course_student_all.shape

Out[4286]: (32446, 30)

In [4287]: course_student_all.describe()
```

Out[4287]:

	Unnamed: 0	id_student	num_of_prev_attempts	studied_credits
count	32446.000000	3.244600e+04	32446.000000	32446.000000
mean	16223.500000	7.062130e+05	0.163163	79.671916
std	9366.497754	5.486818e+05	0.479707	41.027368
min	1.000000	3.733000e+03	0.000000	30.000000
25%	8112.250000	5.084160e+05	0.000000	60.000000
50%	16223.500000	5.900790e+05	0.000000	60.000000
75%	24334.750000	6.441362e+05	0.000000	120.000000
max	32446.000000	2.698591e+06	6.000000	655.000000

	date_registration	date_unregistration	module_presentation_length
count	32446.00000	10024.000000	32446.000000
mean	-69.42375	50.305866	255.988442
std	49.27415	82.044471	13.182773
min	-322.00000	-317.000000	234.000000
25%	-100.00000	-1.000000	241.000000
50%	-57.00000	29.000000	262.000000
75%	-29.00000	109.000000	268.000000
max	167.00000	444.000000	269.000000

	Distinction	Fail	Pass	...	course_n_type
count	32446.000000	32446.000000	32446.000000	...	32446.000000
mean	0.093201	0.216914	0.380941	...	2.664304
std	0.290718	0.412150	0.485626	...	0.472241
min	0.000000	0.000000	0.000000	...	2.000000
25%	0.000000	0.000000	0.000000	...	2.000000
50%	0.000000	0.000000	0.000000	...	3.000000

```
75%        0.000000      0.000000      1.000000      ...             3.000000
max        1.000000      1.000000      1.000000      ...             3.000000

       course_n_Exam  course_n_CMA  course_n_TMA  course_weight_total  \
count   32446.000000  32446.000000  32446.000000         32446.000000
mean        1.135548      3.819978      4.983141           205.754176
std         0.342314      2.885440      0.950003            45.853054
min         1.000000      0.000000      3.000000           100.000000
25%         1.000000      0.000000      4.000000           200.000000
50%         1.000000      5.000000      5.000000           200.000000
75%         1.000000      7.000000      6.000000           200.000000
max         2.000000      7.000000      6.000000           300.000000

       course_weight_Exam  course_weight_CMA  course_weight_TMA  \
count        32446.000000       32446.000000       32446.000000
mean             0.561595           0.020615           0.417790
std              0.139548           0.035347           0.148151
min              0.500000           0.000000           0.000000
25%              0.500000           0.000000           0.375000
50%              0.500000           0.000000           0.500000
75%              0.500000           0.025000           0.500000
max              1.000000           0.125000           0.500000

       course_activity_n  course_site_n
count       32446.000000   32446.000000
mean           11.020249     321.058312
std             2.649248     139.315641
min             7.000000     106.000000
25%            10.000000     207.000000
50%            10.000000     315.000000
75%            11.000000     453.000000
max            16.000000     529.000000

[8 rows x 21 columns]
```

Subset for cutting off point

- Remove those who registered after cut-off point
- Remove those who unregistered before cut-off point

```
In [4288]: course_student_final = course_student_all[course_student_all['date_registration'] <

In [4289]: course_student_final = course_student_final\
           [(course_student_final['date_unregistration'].isnull()) | (course_student_final['dat

In [4290]: course_student_final.shape

Out[4290]: (24678, 30)
```

3.3.2 2) Assessment table

```
In [4291]: assessment_student_all.shape

Out[4291]: (173912, 25)

In [4292]: assessment_student_all.describe()

Out[4292]:           Unnamed: 0  id_assessment    id_student  date_submitted  \
           count  173912.000000  173912.000000  1.739120e+05   173912.000000
           mean    86956.500000   26553.803556  7.051507e+05      116.032942
           std     50204.214345    8829.784254  5.523952e+05       71.484148
           min         1.000000    1752.000000  6.516000e+03      -11.000000
           25%     43478.750000   15022.000000  5.044290e+05       51.000000
           50%     86956.500000   25359.000000  5.852080e+05      116.000000
           75%    130434.250000   34883.000000  6.344980e+05      173.000000
           max    173912.000000   37443.000000  2.698588e+06      608.000000

                      is_banked          score           date         weight  \
           count  173912.000000  173912.000000  173912.000000  173912.000000
           mean        0.010977      75.724171     132.727006      12.743899
           std         0.104194      18.940093      79.110198      17.877301
           min         0.000000       0.000000      12.000000       0.000000
           25%         0.000000      65.000000      54.000000       0.000000
           50%         0.000000      80.000000     131.000000       9.000000
           75%         0.000000      90.000000     222.000000      18.000000
           max         1.000000     100.000000     269.000000     100.000000

                            CMA           Exam      ...        course_n_assessment  \
           count  173912.000000  173912.000000      ...              173912.000000
           mean        0.405533       0.028514      ...                  10.770614
           std         0.490996       0.166438      ...                   2.680086
           min         0.000000       0.000000      ...                   5.000000
           25%         0.000000       0.000000      ...                  10.000000
           50%         0.000000       0.000000      ...                  12.000000
           75%         1.000000       0.000000      ...                  13.000000
           max         1.000000       1.000000      ...                  14.000000

                  course_n_Exam   course_n_CMA   course_n_TMA  number_of_assess  \
           count  173912.000000  173912.000000  173912.000000     173912.000000
           mean        1.108906       4.608710       5.052998          4.921518
           std         0.311522       2.672168       0.940125          3.146100
           min         1.000000       0.000000       3.000000          1.000000
           25%         1.000000       4.000000       5.000000          2.000000
           50%         1.000000       5.000000       5.000000          4.000000
           75%         1.000000       7.000000       6.000000          7.000000
           max         2.000000       7.000000       6.000000         14.000000

                  number_of_assess_r  number_of_assess_lag      score_lag      score_dif  \
```

```
count       173912.000000          173912.000000  148069.000000  148069.000000
mean             4.921518               3.921518      76.729511      -0.515550
std              3.146100               3.146100      18.085162      19.450793
min              1.000000               0.000000       0.000000    -100.000000
25%              2.000000               1.000000      67.000000     -11.000000
50%              4.000000               3.000000      80.000000       0.000000
75%              7.000000               6.000000      90.000000      10.000000
max             14.000000              13.000000     100.000000     100.000000

         total_score
count  173912.000000
mean        9.088426
std        12.750937
min         0.000000
25%         0.000000
50%         6.230000
75%        13.650000
max       100.000000

[8 rows x 22 columns]
```

Subset for cutting off point

- Only keep the results happened before cut-off point

```
In [4293]: assessment_student = assessment_student_all[assessment_student_all['date_submitted'
```

Create the last score variables

- Last score before cut-off point

```
In [4294]: assessment_student['number_of_assess_r'] = assessment_student.groupby(['code_module
           ['date_submitted'].rank(ascending=False, method='first')

In [4295]: last_score = assessment_student[assessment_student['number_of_assess_r'] == 1]

In [4296]: last_score = last_score[['code_module','code_presentation','id_student','score','CM

In [4297]: last_score = last_score.rename(columns={'score': 'last_score', 'CMA': 'last_cma','TM
```

Create aggregate attributes

```
In [4298]: agg_assess = {'score': {'mean_score':'mean', 'sd_score': 'std', 'n_assess':'count'}
                         'score_dif':{'ma_score':'mean'},\
                         'total_score': {'cum_total_score':'sum'},\
                         'Exam': {'n_exam':'sum'},\
                         'CMA': {'n_cma':'sum'},\
                         'TMA': {'n_tma':'sum'},\
                         'is_banked':{'is_banked':'mean'}}
```

```
In [4299]: assessment_student_final = assessment_student.groupby(['code_module','code_presentat
           agg(agg_assess)

In [4300]: assessment_student_final.columns = assessment_student_final.columns.droplevel()
           assessment_student_final = assessment_student_final.reset_index()

In [4301]: # get the percentile for cumscore/meanscore
           assessment_student_final['percentile_cum_score'] = assessment_student_final.\
           groupby(['code_module','code_presentation'])['cum_total_score'].rank(pct = True)
           assessment_student_final['percentile_mean_score'] = assessment_student_final.\
           groupby(['code_module','code_presentation'])['mean_score'].rank(pct = True)

In [4302]: # match last score
           assessment_student_final = assessment_student_final.merge(last_score, how='left')

In [4303]: assessment_student_final.shape

Out[4303]: (25782, 18)
```

3.3.3 3) Interaction table

```
In [4304]: vle_student_all.shape

Out[4304]: (8459320, 18)

In [4305]: vle_student_all.describe()

Out[4305]:          Unnamed: 0    id_student       id_site           date     sum_click  \
           count  8.459320e+06  8.459320e+06  8.459320e+06  8.459320e+06  8.459320e+06
           mean   4.229660e+06  7.332399e+05  7.351661e+05  9.393650e+01  4.066844e+00
           std    2.441995e+06  5.846966e+05  1.307907e+05  7.598022e+01  9.756265e+00
           min    1.000000e+00  6.516000e+03  5.267210e+05 -2.500000e+01  1.000000e+00
           25%    2.114831e+06  5.057670e+05  6.735190e+05  2.400000e+01  1.000000e+00
           50%    4.229660e+06  5.875500e+05  7.300350e+05  8.500000e+01  2.000000e+00
           75%    6.344490e+06  6.459970e+05  8.327600e+05  1.550000e+02  4.000000e+00
           max    8.459320e+06  2.698588e+06  1.049562e+06  2.690000e+02  6.977000e+03

                     week_from       week_to  course_activity_n  course_site_n  \
           count  1.223593e+06  1.223593e+06       8.459320e+06   8.459320e+06
           mean   1.053743e+01  1.056458e+01       1.196184e+01   3.649144e+02
           std    8.373725e+00  8.352738e+00       2.826548e+00   1.412495e+02
           min    0.000000e+00  0.000000e+00       7.000000e+00   1.060000e+02
           25%    3.000000e+00  3.000000e+00       1.000000e+01   2.230000e+02
           50%    9.000000e+00  9.000000e+00       1.100000e+01   4.280000e+02
           75%    1.800000e+01  1.800000e+01       1.500000e+01   4.780000e+02
           max    2.900000e+01  2.900000e+01       1.600000e+01   5.290000e+02

                  subpage_click  homepage_click  oucontent_click  forumng_click  \
           count   8.459320e+06    8.459320e+06     8.459320e+06   8.459320e+06
```

```
mean    4.032927e-01    8.214684e-01    1.248183e+00    5.744468e-01
std     1.733989e+00    3.838690e+00    5.660596e+00    2.288682e+00
min     0.000000e+00    0.000000e+00    0.000000e+00    0.000000e+00
25%     0.000000e+00    0.000000e+00    0.000000e+00    0.000000e+00
50%     0.000000e+00    0.000000e+00    0.000000e+00    0.000000e+00
75%     0.000000e+00    0.000000e+00    0.000000e+00    0.000000e+00
max     3.958000e+03    6.977000e+03    3.725000e+03    4.030000e+02

       resource_click     url_click
count    8.459320e+06  8.459320e+06
mean     1.262428e-01  6.699144e-02
std      3.015881e+00  4.029106e-01
min      0.000000e+00  0.000000e+00
25%      0.000000e+00  0.000000e+00
50%      0.000000e+00  0.000000e+00
75%      0.000000e+00  0.000000e+00
max      4.953000e+03  3.580000e+02
```

Subset for cutting off point

- Only keep the results happened before cut-off point

```
In [4306]: vle_student = vle_student_all[vle_student_all['date'] < cutoff_i]
```

Create aggregate attributes

```
In [4307]: agg_vle = {'date':{'total_active_day': 'nunique'},\
                      'id_site': {'total_site':'count','total_uni_site': 'nunique'},\
                      'subpage_click': {'total_visit_subpage':'count', 'total_click_subpage':'s
                      'homepage_click': {'total_visit_homepage':'count', 'total_click_homepage
                      'oucontent_click': {'total_visit_oucontent':'count', 'total_click_ouconte
                      'forumng_click': {'total_visit_forumng':'count','total_click_forumng':'su
                      'resource_click': {'total_visit_resource':'count', 'total_click_resource
                      'url_click': {'total_visit_url':'count', 'total_click_url':'sum'}} #'dat

In [4308]: vle_student_final = vle_student.groupby(['code_module','code_presentation','id_stude
           agg(agg_vle)

In [4309]: vle_student_final.columns = vle_student_final.columns.droplevel()
           vle_student_final = vle_student_final.reset_index()

In [4310]: vle_student_final.shape

Out[4310]: (29195, 18)
```

3.4 1.4 Select variables for independent variables

3.4.1 Drop variables - used to fine-tune variables easily

```
In [4311]: assessment_student_final.columns
```

```
Out[4311]: Index([u'code_module', u'code_presentation', u'id_student', u'n_exam',
                  u'cum_total_score', u'is_banked', u'n_cma', u'n_tma', u'mean_score',
                  u'sd_score', u'n_assess', u'ma_score', u'percentile_cum_score',
                  u'percentile_mean_score', u'last_score', u'last_cma', u'last_tma',
                  u'last_exam'],
                 dtype='object')

In [4312]: assessment_student_final = assessment_student_final.\
           drop(['sd_score','ma_score',\
                 'last_exam','n_cma', 'n_tma','n_exam','mean_score','cum_total_score'], axis=1)

In [4313]: vle_student_final.columns

Out[4313]: Index([u'code_module', u'code_presentation', u'id_student', u'total_uni_site',
                  u'total_site', u'total_click_forumng', u'total_visit_forumng',
                  u'total_click_url', u'total_visit_url', u'total_click_resource',
                  u'total_visit_resource', u'total_active_day', u'total_click_subpage',
                  u'total_visit_subpage', u'total_click_oucontent',
                  u'total_visit_oucontent', u'total_visit_homepage',
                  u'total_click_homepage'],
                 dtype='object')

In [4314]: #vle_student_final = vle_student_final.\
           #drop(['mean_click_forumng','mean_click_resource','mean_click_url',\
           #      'mean_click_subpage','mean_click_oucontent','mean_click_homepage'], axis=1)

In [4315]: course_student_final.columns

Out[4315]: Index([u'Unnamed: 0', u'code_module', u'code_presentation', u'id_student',
                  u'gender', u'region', u'highest_education', u'imd_band', u'age_band',
                  u'num_of_prev_attempts', u'studied_credits', u'disability',
                  u'final_result', u'date_registration', u'date_unregistration',
                  u'module_presentation_length', u'Distinction', u'Fail', u'Pass',
                  u'Withdrawn', u'course_n_type', u'course_n_Exam', u'course_n_CMA',
                  u'course_n_TMA', u'course_weight_total', u'course_weight_Exam',
                  u'course_weight_CMA', u'course_weight_TMA', u'course_activity_n',
                  u'course_site_n'],
                 dtype='object')

In [4316]: course_student_final = course_student_final.\
           drop(['Unnamed: 0','region','final_result','module_presentation_length','Distinctio
                'Pass','Withdrawn', u'course_n_type', u'course_weight_total', u'course_weight_
                 u'course_weight_CMA', u'course_weight_TMA', u'course_activity_n',
                 u'course_site_n'], axis=1)
           #must keep 3 PK and 2 date
           if (metric == 'Withdrawn'):
               course_student_final = course_student_final.drop(['Fail'], axis=1)
```

3.4.2 Merge all tables together

```
In [4317]: dataset = course_student_final.merge(vle_student_final, how='left', on=['code_module

In [4318]: dataset = dataset.merge(assessment_student_final, how='left', on=['code_module', 'co

In [4319]: dataset['p_assess'] = dataset['n_assess']/ (dataset['course_n_Exam'] + dataset['cour

In [4320]: dataset = dataset.drop(['n_assess','course_n_Exam','course_n_CMA','course_n_TMA'], a

In [4321]: dataset.shape

Out[4321]: (24678, 35)
```

3.4.3 Convert categorical data into dummy variables

- Here I've tried both one-hot encoding for all categorical variables, and converted some categorical variables into numeric when the relationship is ordinal (like age, region level and education)
- The results do not differ much. In reality, tree-based model is better to handle numeric variables than many categorical one, especially if the tree is shallow, categorical variables are less likely to be used up
- Reference: https://medium.com/data-design/visiting-categorical-features-and-encoding-in-decision-trees-53400fa65931

```
In [4322]: cleanup_nums = {"age_band":     {"0-35": 1, "35-55": 2, "55<=": 3},
                           "imd_band": {"0-10%": 1, "10-20": 2, "20-30%": 3, "30-40%": 4,"40-50
                                        "50-60%": 6, "60-70%": 7, "70-80%":8, "80-90%":9,
                           "highest_education": {"No Formal quals": 1, "Lower Than A Level": 2
                                                 "HE Qualification": 3, "A Level or Equivalent"

In [4323]: dataset.replace(cleanup_nums, inplace=True)

In [4324]: cols_to_transform = ['code_module','code_presentation','gender','disability'] #'code

In [4325]: dataset_final = pd.get_dummies(dataset, columns = cols_to_transform, drop_first=True
```

3.4.4 For withdrawal case, adjust the window

```
In [4326]: if (metric == 'Withdrawn') & (cutoff_i <30):
               dataset_final['Withdrawn'] = np.where((dataset_final['date_unregistration'] < cu
           elif (metric == 'Withdrawn') & (cutoff_i >= 30):
               dataset_final['Withdrawn'] = np.where((dataset_final['date_unregistration'] < cu

In [4327]: dataset_final = dataset_final.fillna(0) #fill in all missing values with 0
```

3.5 1.5 Split train and test

- As I don't put the historical data (i.e. the information happen in previous term), the train test split is purly random, rather than leaving out results in 2014J.

```
In [4328]: X = dataset_final.drop([metric,'date_unregistration','id_student'], axis=1)
           y = dataset_final[metric]

In [4329]: X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=.3, random_sta

In [4330]: X_train.shape, X_test.shape

Out[4330]: ((17274, 39), (7404, 39))

In [4331]: y_train.shape, y_test.shape

Out[4331]: ((17274,), (7404,))

In [4332]: np.mean(y_train), np.mean(y_test) #label % in two groups, for QC

Out[4332]: (0.28291073289336577, 0.29038357644516477)

In [4333]: X_train.columns #final labels, for QC

Out[4333]: Index([u'highest_education', u'imd_band', u'age_band', u'num_of_prev_attempts',
                  u'studied_credits', u'date_registration', u'total_uni_site',
                  u'total_site', u'total_click_forumng', u'total_visit_forumng',
                  u'total_click_url', u'total_visit_url', u'total_click_resource',
                  u'total_visit_resource', u'total_active_day', u'total_click_subpage',
                  u'total_visit_subpage', u'total_click_oucontent',
                  u'total_visit_oucontent', u'total_visit_homepage',
                  u'total_click_homepage', u'is_banked', u'percentile_cum_score',
                  u'percentile_mean_score', u'last_score', u'last_cma', u'last_tma',
                  u'p_assess', u'code_module_BBB', u'code_module_CCC', u'code_module_DDD',
                  u'code_module_EEE', u'code_module_FFF', u'code_module_GGG',
                  u'code_presentation_2013J', u'code_presentation_2014B',
                  u'code_presentation_2014J', u'gender_M', u'disability_Y'],
                 dtype='object')
```

4 Part 2. Model Building

4.0.1 2.1 Random Forest

```
In [4334]: if algorithm == "Random Forest":
               rf = RandomForestClassifier(random_state=12345)
               rf_grid = {'n_estimators':[60, 80],'max_depth':[8,10], 'max_features':[8,12]} #

               rf_cv = GridSearchCV(estimator=rf, param_grid=rf_grid, cv=5, scoring='f1')
               rf_final = rf_cv.fit(X_train, y_train)

               y_pred = rf_final.predict(X_test)
               y_pred_p = rf_final.predict_proba(X_test)
               print rf_cv.best_params_
```

```
{'max_features': 12, 'n_estimators': 60, 'max_depth': 10}
```

4.0.2 2.2 XGBoost

- XGBoost has similar performance as random forest. Considering the calculation speed, random forest will be used as final model

```
In [4335]: if algorithm == "XGBoost":
               reg = XGBClassifier(seed=12345,silent=0)
               reg_pram = {'n_estimators':[80,100],'learning_rate':[0.01, 0.1],'subsample':[0.
               reg_search = GridSearchCV(reg, reg_pram, cv = 5, scoring='f1')
               reg_final = reg_search.fit(X_train, y_train)
               y_pred = reg_final.predict(X_test)
               y_pred_p = reg_final.predict_proba(X_test)
```

4.0.3 2.3 Neural Network

- Neural network provides slightly better performance. However as it is a black box model that cannot provide the feature importance, I didn't use it for final model

```
In [4336]: import keras
           from keras.layers import Dense
           from keras.models import Sequential
           from keras.utils import to_categorical
```

```
In [4337]: if algorithm == "Neural Network":
               # Save the number of columns in predictors: n_cols
               n_cols = X_train.shape[1]
               input_shape = (n_cols,)

               # Specify the model
               model = Sequential()
               model.add(Dense(60, activation='relu', input_shape = input_shape))
               model.add(Dense(30, activation='relu'))
               model.add(Dense(1, activation='sigmoid'))

               # Compile the model
               model.compile(optimizer='adam',loss = 'binary_crossentropy', metrics=['accuracy

               # Define early_stopping_monitor
               #early_stopping_monitor = EarlyStopping(patience=2) #generally it's 2 to 3

               # Fit the model
               model.fit(X_train.values,y_train.values,epochs=30,validation_split=0.3) #,callb
               y_pred = model.predict_proba(X_test.values)
```

4.0.4 2.4 Feature importance (from random forest)

```
In [4338]: if algorithm == "Random Forest":
               feature_importance_rf = dict(zip(X_train.columns,rf_final.best_estimator_.featu
               print sorted([(value,key) for (key,value) in feature_importance_rf.items()])
```

```
[(0.12768055398519079, 'code_module_EEE'), (0.13242089451797037, 'last_cma'), (0.16397364033273
```

5 Part 3. Model Evaluation

5.0.1 3.1 Basic model performance

- Here the basic performance is printed for easily refer. However for our case, cutting off the positive case at probability 0.5 (by default setting in classification problem) is not helpful for targeting. Thus I will use KS statistic to evaluate performance, and cumulative gain chart to show the % of positive cases among those who are targeted.

```
In [4339]: print 'Accuracy of model:', accuracy_score(y_test, y_pred)
           print 'Classification report of model:'
           print classification_report(y_test, y_pred)
           print 'Confusion matrix'
           tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
           print (tn, fp, fn, tp)
```

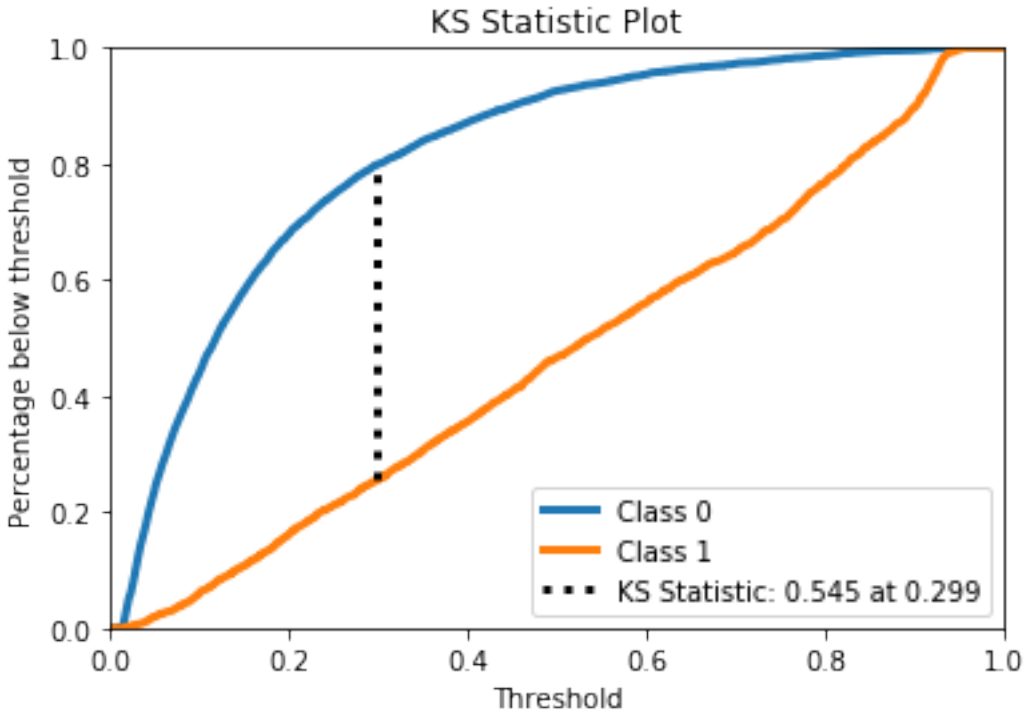
```
Accuracy of model: 0.811993517018
Classification report of model:
             precision    recall  f1-score   support

          0       0.83      0.93      0.87      5254
          1       0.75      0.53      0.62      2150

avg / total       0.81      0.81      0.80      7404

Confusion matrix
(4865, 389, 1003, 1147)
```

5.0.2 3.2 KS statistics

- K-S is a measure of the degree of separation between the positive and negative distributions. The K-S is 100, if the scores partition the population into two separate groups in which one group contains all the positives and the other all the negatives.
- Reference: https://www.analyticsvidhya.com/blog/2016/02/7-important-model-evaluation-error-metrics/

```
In [4340]: import matplotlib.pyplot as plt
           import scikitplot as skplt
```

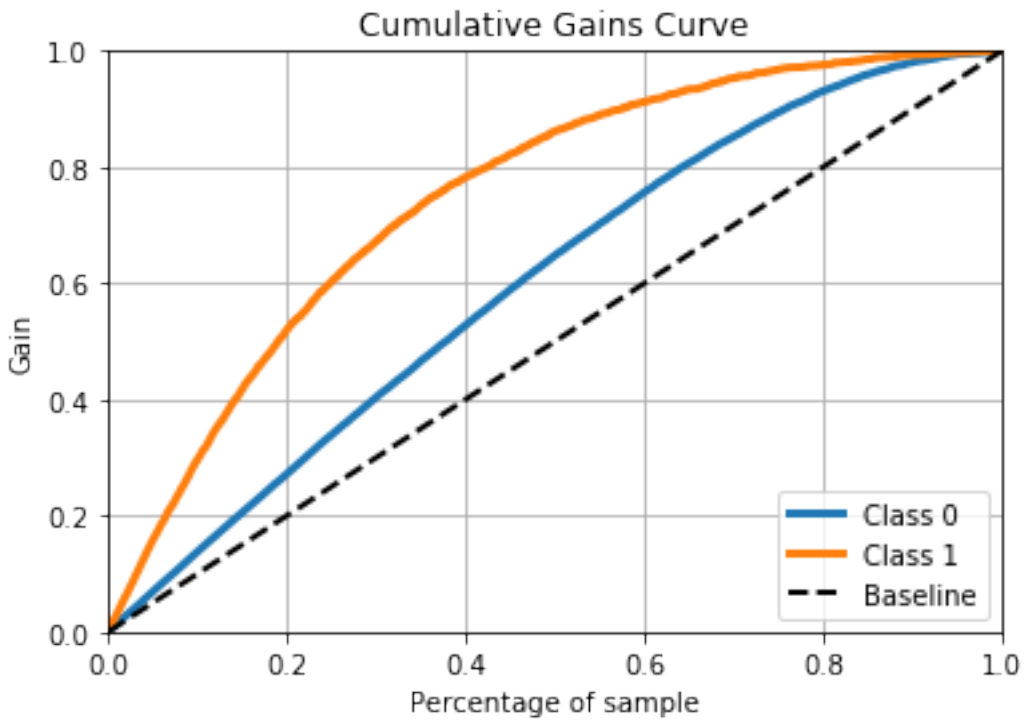
In [4341]:
```
skplt.metrics.plot_ks_statistic(y_test, y_pred_p)
plt.show()
```



5.0.3 3.3 Cumulative gain charts

- Gain chart shows that for different % of targeted samples, what is the % of positive cases among all samples targeted
- Reference: http://mlwiki.org/index.php/Cumulative_Gain_Chart

In [4342]:
```
skplt.metrics.plot_cumulative_gain(y_test, y_pred_p)
plt.show()
```




```
In [4343]: #skplt.estimators.plot_learning_curve(rf_final.best_estimator_, X_train, y_train)
           #plt.show()
```

Getting the data for charting...

- Reference: https://github.com/reiinakano/scikit-plot/blob/master/scikitplot/helpers.py
- Here I get the gain calculation directly from the code source from scikitplot package

```
In [4344]: def cumulative_gain_curve(y_true, y_score, pos_label=None):
               y_true, y_score = np.asarray(y_true), np.asarray(y_score)

               # ensure binary classification if pos_label is not specified
               classes = np.unique(y_true)
               if (pos_label is None and
                   not (np.array_equal(classes, [0, 1]) or
                        np.array_equal(classes, [-1, 1]) or
                        np.array_equal(classes, [0]) or
                        np.array_equal(classes, [-1]) or
                        np.array_equal(classes, [1]))):
                   raise ValueError("Data is not binary and pos_label is not specified")
               elif pos_label is None:
                   pos_label = 1.

               # make y_true a boolean vector
```

```
    y_true = (y_true == pos_label)

    sorted_indices = np.argsort(y_score)[::-1]
    y_true = y_true[sorted_indices]
    gains = np.cumsum(y_true)

    percentages = np.arange(start=1, stop=len(y_true) + 1)

    gains = gains / float(np.sum(y_true))
    percentages = percentages / float(len(y_true))

    gains = np.insert(gains, 0, [0])
    percentages = np.insert(percentages, 0, [0])

    return percentages, gains
```

```
In [4345]: percentages, gains = cumulative_gain_curve(y_test, y_pred_p[:, 1])

In [4346]: gain_result = DataFrame(gains)

In [4347]: percentages_result = DataFrame(percentages)

In [4348]: final_metric = pd.concat([percentages_result, gain_result], axis=1)

In [4349]: #final_metric.to_csv("~/Google Drive/MSBA@UMN/OULAD/cumulative_gain_withdraw.csv")
```