Predicting Student Success Using Virtual Learning Environment Interaction Statistics

In [1]:

```
%load_ext autoreload
%autoreload 2

import pandas as pd
import numpy as np

from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
, KFold
from sklearn.metrics import confusion_matrix, accura
cy_score, classification_report

from xgboost import XGBClassifier

from imblearn.over_sampling import SMOTE

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import os
import sys
module_path = os.path.abspath(os.path.join(os.pardir
))
if module_path not in sys.path:
    sys.path.append(module_path)
from src.functions import load_OU_data, CourseScaler
, plot_confusion, score_grid, \
smotecourses, process_courses, course_cross_validate
, Course_GridSearchCV, \
registration_correlations, dist_by_course

from dython.nominal import associations

import pickle

import warnings

warnings.filterwarnings("ignore")
sns.set_style('whitegrid')

pd.set_option('display.max_columns', None)
sns.set(font_scale=1.5)
```

The Problem

Online learning has been a growing and maturing industry for years now, and in a way the internet has always been about learning. Khan Academy (https://www.khanacademy.org/) is, to me, a quintessential step in self-driven learning and massive open online courses (MOOCs) like Coursera (https://www.coursera.org/) create an even more structured approach to online, self-drive learning. I took my first online course on coding fundamentals from edX (https://www.edx.org/) in 2013.

While these are an amazing resources, they also have a high dropout and failure rate. Many students, accustomed to the accountability features in traditional face-to-face learning, struggle with the open-ness of these systems and the lack of a person keeping us accountable. It can be easy to get lost or give up.

I set out to find ways to use data to help online courses improve student success by identifying students who are in danger of failing or withdrawing early. My theory is that students in need of special intervention to improve their chances of success can be identified by the way they interact with the online learning system itself.

The goal of this project is to model student interactions with an online learning environment to predict whether they will ultimately pass or fail the course at the half-way point of the course, in time for an intervention to be staged. My goal is to make this model generalizable by removing correlations with specific courses and instead capturing the underlying functions that can predict the success of students in any self-paced online learning

environment. I believe many students who are struggling will exhibit particular patterns of behavior in how they interact with the learning environment.

My Hypothesis:

I would like to test my theory that spreading learning out among more days, rather than cramming into fewer days, positively affects learning outcomes. If I am correct, we should see the number of discrete days that a student studied being highly predictive of their final success.

The Data

I used a dataset from Open University (http://www.openuniversity.edu/) based out of Great Britain. They are an entirely online university offering accredited degrees to distance learners. They released anonymized data from seven courses, three from the social sciences and four STEM courses, from the 2013 and 2014 academic year. These courses are repeated twice per year and each repetition is call a 'presentation'. Not all presentations of each course are included in the dataset. To learn more about how the data was selected and anonymised, please visit this US National Institute of Health (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5704676/) site that holds the data for scientific inquiry.

This dataset contains regional, demographic, and personal data about students, but I was only interested in data about how they interacted with the learning environment. The university provided information about each activity that each student interacted with, including the date and number of clicks on that activity in StudentVle.csv available in the anonymiseData.zip (content/anonymisedData.zip) file in the form of individual activity engagements. I aggregated those interactions into the following three features:

1. Number of total clicks during the presentation of the course.
2. Number of total activities completed
3. Number of days worked

It was the last statistic that I felt would be uniquely predictive. I spent 14 years teaching students and one thing I learned from research and experience is that spreading learning out over more days, rather than cramming more learning on fewer days, helps with persistence and with learning retention. It helps with persistence because it causes the student to form a habit of learning. We are creatures of habit. Cramming a lot of learning

into fewer days is also more exhausting and less pleasant, creating a sense of aversion to the act. Frequent reinforcement of learning also serves to reinforce neuronal axons that are the physical manifestation of learning. I'll show what I found on this later on in this notebook.

The next statistics I pulled to use to train my model were from studentAssessments.csv and represented the number and average score of assessments that they student completed. Courses contained between 7 and 12 assessments.

Assessment Statistics

1. Average assessment score
2. Number of assessments completed.

The first was an obvious choice, and the second is meaningful because these courses were self-paced.

1. Course Repetition

The final statistic I took was the number of times the student had repeated the same course. To be completely honest this is not data directly from interactions, and is in fact a sort of meta-data. However it should be available in any learning environement that tracks student histories across courses.

Data Preparation

I took several steps in order to prepare the data for exploration and modeling.

1. I merged the 7 tables in the provided zip file.
2. I cleaned the data of rows with values missing in important columns, or suspicious values such as student withdrawing before they register or withdrawing after the end of the course.
3. I extracted statistics on the virtual learning environment interaction data as new features, see above.
4. I extracted statistics on assessments as new features, see above.
5. I enabled the data preparation function to filter a prediction window that would limit the data to registration records for students whom completed the course or withdrew after the prediction window and limited the extracted statistics to those assessment and interaction records occurring previous to the the end of the prediction window. This allows for predictions to be made at particular points in the course. Predicting later in the course increases model accuracy while predicting earlier allows for earlier intervention and the possibility

for interventions for students who would withdraw earlier in the course.

Data Exploration

Let's take a look at the shape and general statistics of the data. We will drop the columns our model will not use. They were useful to explore some correlations between demographics and outcomes, but are not relevant to our actual modeling. If you want to see more about what I found in that exploration, please see my EDA notebook (../notebooks/OU_eda.ipynb)

Here I will focus on correlations within the activity and assessment statistics that I will be using for modeling.

The data below represent the entire dataset, not just the prediction window I will be using for modeling.

In [2]:

```
df = load_OU_data(prediction_window = None)
df.drop(columns = ['id_student','code_presentation',
'region','highest_education', \
                   'imd_band','gender','age_band','d
isability','studied_credits',
                   'module_presentation_length','dat
e_registration'], inplace = True)
if 'date_unregistration' in df.columns:
    df.drop(columns = ['date_unregistration'], inpla
ce = True)
df.head()
```

Out[2]:

	code_module	num_of_prev_attempts	final_result	days_
0	AAA	0	Pass	40.0
1	AAA	0	Pass	80.0
2	AAA	0	Withdrawn	12.0
3	AAA	0	Pass	123.0
4	AAA	0	Pass	70.0

In [4]:

```
df.describe()
```

Out[4]:

	num_of_prev_attempts	days_studied	activities_enga
count	28430.000000	28430.000000	28430.000000

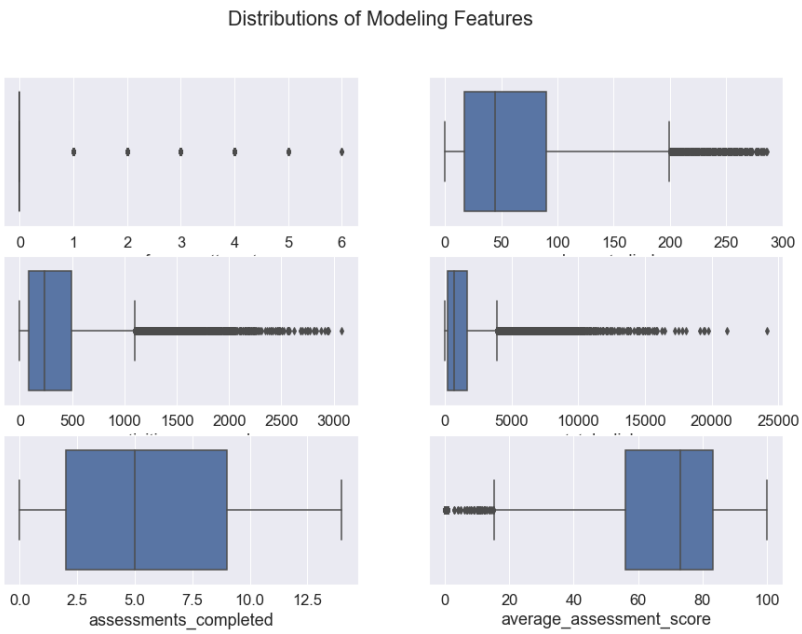
mean	0.161977	60.103904	352.992332
std	0.476656	53.703165	374.433547
min	0.000000	0.000000	0.000000
25%	0.000000	17.000000	87.000000
50%	0.000000	45.000000	232.000000
75%	0.000000	90.000000	492.000000
max	6.000000	286.000000	3078.000000

We see here some very large standard deviations in some of these statistics. Notice that `total_clicks` ranges from 1 to 24139 and activities engaged ranges from 1 to 3078. Let's further explore these distributions

In [5]:

```
fig, axes = plt.subplots(3,2, figsize = (15,10))
columns = [ 'num_of_prev_attempts', 'days_studied',
       'activities_engaged', 'total_clicks', 'assess
ments_completed',
       'average_assessment_score']
for i, ax in enumerate(axes.ravel()):

    sns.boxplot(df[columns[i]], ax=ax)
plt.suptitle('Distributions of Modeling Features')
plt.show()
```



There are definitely some outliers, students who clicked an order of magnitude more than the average. We also see few students who repeated the course. The distribution of `activities_engaged` makes me wonder how many activities

were available in the courses and whether my data includes activities that were engaged on more than one occasion. I'm actually not going to remove any of these outliers. That may or may not be the right decision and in future iterations I may try doing so after all.

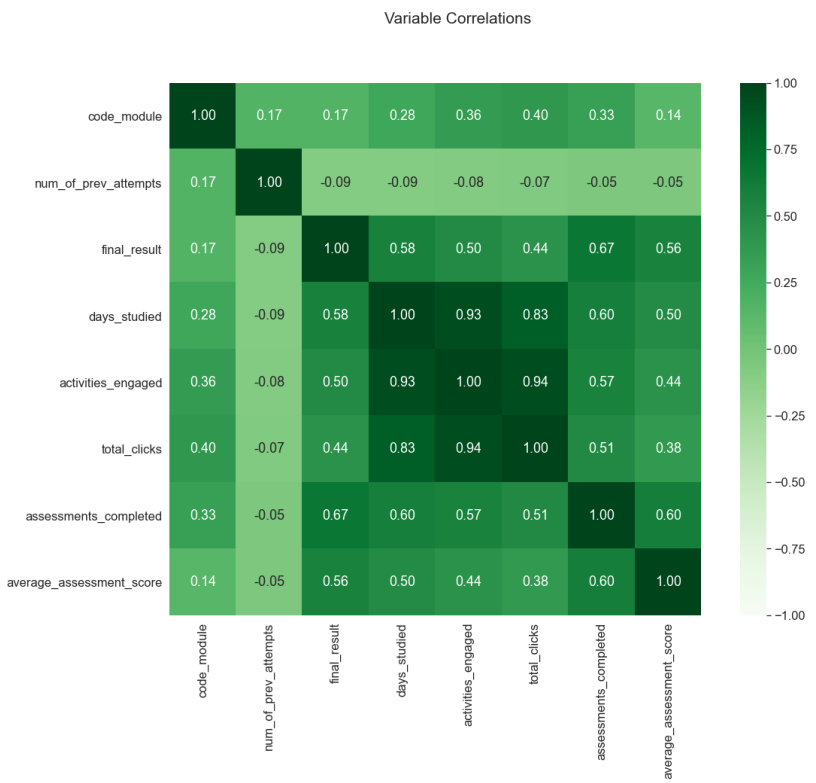
Correlations:

I am indebted to Shaked Zychlinsk and his dython module (https://github.com/shakedzy/dython) for the below correlation matrix function, which uses his `associations()` function internally. Please refer to the documentation of the `dython.nominal.associations` to see how it chooses the right kind of correlation for each box, depending on whether its categorical/categorical, nominal/categorical, or nominal/nominal.

One note: `registration_correlations()` is turning `final_results` into a nominal variable with higher numbers being better outcomes. This helps us see not just how much another variable affects the results, but in what direction it drives it.

In [6]:

```
registration_correlations(df, cmap = 'Greens', save_
path = '../figures/coursecorr.png')
```



The good news and the bad news

First the good

1. In fact all of our activity and assessment statistics have strong correlations with the final result. `num_of_prev_attempts` is weakly and negatively correlated, but does seem to make some difference.
2. `days_studied` is only topped by number of assessments completed for most correlated, which feels like a win for my hypothesis above. It's even more highly correlated than assessment scores!
3. `total_clicks` is not as highly correlated as the other activity statistics. This is interesting and may be an area of future study.

Now the bad

1. Our activity stats are all very highly correlated to each other, and this stands to reason. The more days you study, the more activities you engage. The more activities you engage, the more times you click. `assessments_completed` and `average_assessment_score` are also correlated, but not as strongly as one might thing. This high correlation between features would be a problem if we were doing inferential modeling, such as OLS, but it's fine for predictive modeling. If we want to do inferences we would probably have to just pick one of those (`days_studied` would be my candidate).
2. The activity stats and assessment stats are correlated to `code_module`. This leads me to believe that different courses have different numbers of assessments and different numbers of essential activities. This also stands to reason, why would all the courses be the same? Since I want to extend this model to new courses in new learning systems this correlation is even more important. This bias by course will become a hidden variable that will disrupt future predictions on new courses, and also is outside the scope of what we are trying to accomplish: predicting by activity. We need away way around this.
3. `final_result` is also correlated to `code_module`, which presents another problem. This tells me that different courses have different success rates, which of course is also reasonable. The correlation to our target variable is a separate problem from the correlation to our predictor variables. I will address these troublesome groupings in my data preprocessing later in this notebook.

Prediction Window

A key element of my model is that it is meant to be an early

warning system. It flags students for intervention before the end of the course in order to change their trajectory. The prediction window is easy to change on all of these notebooks as it's a single argument in the data loading function. There is a trade-off though. A wider window not only gives less time for a student to catch up or change their habits, students also continually withdraw from the course. The longer we wait, the more students we lose. On the other hand, more data mean better predictions. The more the model has seen of the students' behavior, the more accurate it can be. Let's take a look at when students leave the programs:

In [ ]:

```
model = pickle.load(open('../models/XGBmodel4.pkl',
'rb'))

window_scores = pd.DataFrame(columns = ['Cross Valid
ated Accuracy','Test Set Accuracy'],
                             index = [x*10 for x in r
ange(1,11,1)])

for window in range(1,11,1):
    window_df = load_OU_data(prediction_window=windo
w/10)
    window_df.drop(columns = ['id_student','code_pre
sentation','region','highest_education', \
                          'imd_band','gender','age_ban
d','disability','studied_credits',
                          'module_presentation_length',
'date_registration'], inplace = True)
    X = window_df.drop('final_result', axis=1)
    y = window_df['final_result']

    y = np.array(['No Intervention' if w in ['Pass',
'Distinction'] \
                  else 'Needs Intervention' for w in
y])

    cv = KFold(shuffle=True, random_state=111)

    X_train, X_test, y_train, y_test = train_test_sp
lit(X,y, random_state = 111, test_size=.2)

    #the cross validator processes data as it's vali
dating, but we want a set for final evaluation, too.
    X_train_transformed, y_train_transformed, X_test
_transformed = process_courses(X_train, y_train, X_t
est)

    scores = course_cross_validate(model, X_train, y
_train, cv=cv, scoring='accuracy', random_state=111)

    best_val_score = np.mean(scores)
    model.fit(X_train_transformed, y_train_transform
ed)
```

```
    y_pred = model.predict(X_test_transformed)
    test_score = accuracy_score(y_test, y_pred)
    window_scores.loc[window * 10, 'Cross Validated
 Accuracy'] = best_val_score * 100
    window_scores.loc[window * 10, 'Test Set Accurac
y'] = test_score * 100

fig, ax = plt.subplots(2,1, figsize = (10,10), share
x=False)
ax = ax.ravel()
window_scores.plot(ylim = (60,100), xlim = (0,100),
                   title = 'Prediction Window / Accur
acy Tradeoff',
                   ax = ax[0])
full_data = load_OU_data(prediction_window=None)
withdrawals = full_data[full_data['final_result'] ==
'Withdrawn']
withdraw_time = withdrawals['date_unregistration']/w
ithdrawals['module_presentation_length'] * 100

sns.kdeplot(data=full_data[full_data.final_result ==
'Withdrawn'], ax = ax[1],
            x=withdraw_time, fill=True, legend=True,
clip = (0,100),
            cumulative = True).set_title('Cumulative
Withdrawals Over Time')
ax[0].set_ylabel('Model Accuracy')
ax[1].set_xlabel('Proportion of Course Elapsed')
ax[1].set_ylabel('Proportion of Withdrawals')
plt.savefig('../figures/accuracy_prediction_window_t
radeoff.png')
```

By the halfway point of the course, over 65% of the students who will withdraw already have. A prediction window of .5 doesn't give the model as much data as a longer window would, but it is also quite late in the course in terms of trying to retain withdrawing students. This notebook, or the model development notebook (../notebooks/shallow_modeling.ipynb) can be run with different prediction windows by changing the `prediction_window` variable in `load_OU_data()` function. The accuracy of my final model over the different predictions windows for this data set is plotted on the lower chart.

Preprocessing

I told you some about preparing the data, but there is more to do to overcome the problems mentioned above.

1. We will limit the data to what makes sense for our prediction window, or the points in the course we want to make our predictions on. For one, we won't try to predict the outcomes of students who have already withdrawn. We also won't use any data that we would not yet have

by that point in the course.
2. Our data target classes are 'Distinction', 'Pass', 'Fail', and 'Withdrawn'. However, our predictor only predicts whether a student needs intervention or not. Those passing or passing with distinction do not need interventions, while those failing or withdrawing do. We will combine the first two into a new class 'No Intervention' and the second two into 'Needs Intervention'. This makes our target binary, easier to predict and easier to evaluate. There is an argument for separating withdrawing students and failing students, but my model is not accurate at differentiating between those.
3. We will scale all the data course by course. The `CourseScaler` class object will fit on each individual course, as indexed by the `code_module` variable. It will take the mean and standard deviation for each feature for each course from the training data and use these to scale each feature for each individual course `(X - mean) / standard deviation` for both the training and the testing data. This will remove the correlations between `code_module` and the activity and assessment statistics.
4. We will use the `smotecourses()` function to apply imblearn.over_sampling.SMOTE (https://imbalanced-learn.org/stable/generated/imblearn.over_sampling.SMOTE.html) to the training data to create synthetic data within the minority class to balance the classes. Each course in the training set will then have equal number of students needing intervention and not needing interventions, even though some of those students are not real, but approximations. This will remove the correlation between `code_module` and `final_result`.
5. Once those are done, we can drop the `code_module` column, because we don't want our model considering that in its predictions.

Let's take a look at how these steps effect our correlation matrix.

Scaling

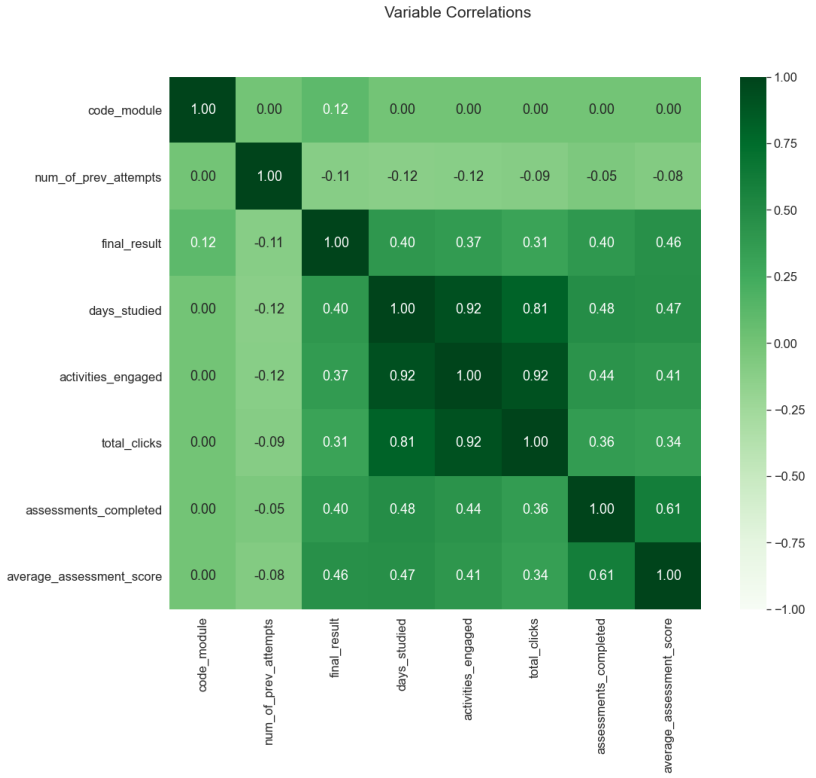
In [3]:

```
#Setting prediction_window to .5 loads data up to th
e halfway point of the shortest course present
half_df = load_OU_data(prediction_window=.5)
half_df.drop(columns = ['id_student','code_presentat
ion','region','highest_education', \
                    'imd_band','gender','age_band','d
isability','studied_credits',
```

```
                    'module_presentation_length','dat
e_registration'], inplace = True)

#Scale the variables, but keep `code_module` for com
paring
cs = CourseScaler(drop_course=False)
scaled_half_df = cs.fit_transform(half_df)

#create the new correlation matrix
registration_correlations(scaled_half_df, cmap = 'Gr
eens', save_path = '../figures/scaledcoursecorr.png'
)
```



By scaling the data by course we have removed the correlations along the top row for most variables. the only thing left is the target variable, `final_result`. We can take care of that by balancing the classes in each course.

SMOTE-ing

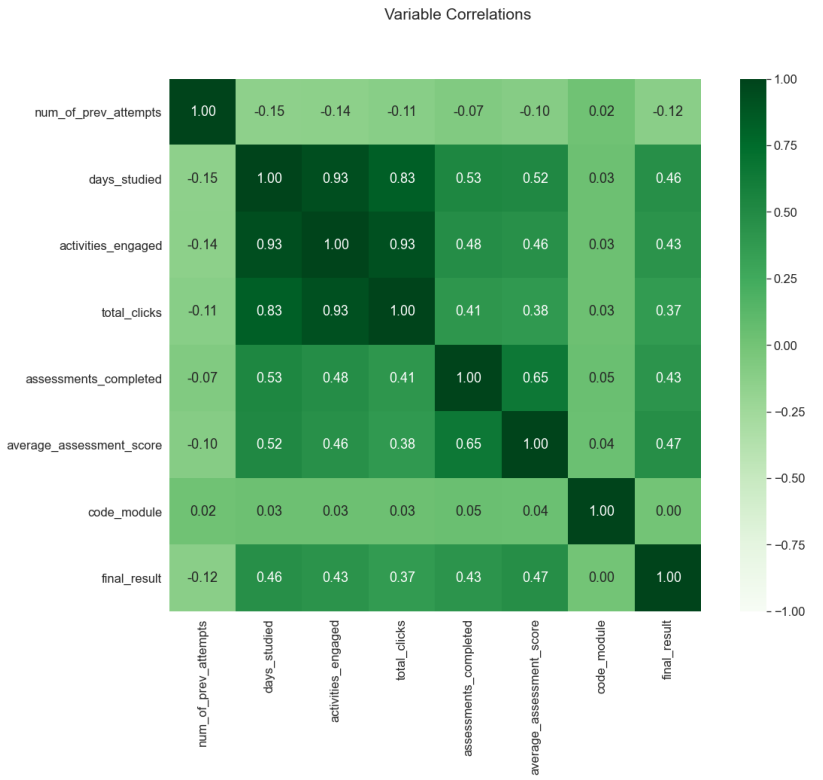
This approach creates synthetic data is that is similar, but not identicial to observations in the minority class of students to balance the classes. The prevents the model from over-predicting one class. Otherwise the model decides that the safer choice, when in doubt, is to guess an observation belongs to the class with the most observations. While this may work for the present dataset, it would not serve the model well for predicting new data where the class balance is different.

In [4]:

```
demo_X = scaled_half_df.drop('final_result', axis=1)
```

```
demo_X = scaled_half_df.drop('final_result', axis=1)
demo_y = scaled_half_df['final_result']

smoted_X, smoted_y = smotecourses(demo_X, demo_y, dr
op_course=False)
smoted_X['final_result'] = smoted_y
registration_correlations(smoted_X, cmap='Greens', s
ave_path = '../figures/scaled_smoted_coursecorrs.pn
g')
```



The smoting process added a small amount of residual correlation between the `code_module` and some of the features, but nothing significant. There is now no correlation between the specific courses and our target variable, `final_result`

Modeling

The heavy lifting here was in the data preparation and preprocessing. We will try a few different models, a logistic regression for a baseline FSM, and then some tree based models, a decision tree, a random forest, an eXtreme Gradient Boost model (because Kagglers love them!), and a support vector machine.

I used a custom Course_GridSearchCV class to do a grid based hyperparameter search to help me set good hyperparameters for each of these. This was needed because my scaler and smoter each need the `code_module` feature in order to do their work, but need to remove it before modeling. This was not possible to do with the sklearn or imblearn pipelines or with with the cross validation functions they offer. So, I wrote my own.

I won't show the whole grid search process here, but if you'd like to see how I did it, please visit my model development notebook (../notebooks/shallow_modeling.ipynb). You can also find a brief discussion of how each model works and links to more information there.

Dividing the Data for Training and Testing

I will divide our dataset into features, `X` and labels, `y`. Then I will collapse the 4 labels into 2 bins, as I discussed before and divide them into training and testing sets.

For all of these models we will use `course_cross_validate()`, which fits a `CourseScaler` object on the training data, and transforms both training and testing data for each fold. Then it will use `smotecourses()` to balance the classes in each course only for the training data for each fold and report the scores. This prevents data leakage into our testing folds from either process and combats overfitting.

In [5]:

```
X = half_df.drop('final_result', axis=1)
y = half_df['final_result']

cv = KFold(n_splits = 5, shuffle=True, random_state=
111)

X_train, X_test, y_train, y_test = train_test_split(
X, y, random_state = 111, test_size=.2)
y_test_uncollapsed = y_test.reset_index(drop=True)
y_train = np.array(['No Intervention' if w in ['Pas
s','Distinction'] \
              else 'Needs Intervention' for w in y_t
rain])
y_test = np.array(['No Intervention' if w in ['Pass'
,'Distinction'] \
              else 'Needs Intervention' for w in y_t
est])

#the cross validator processes data as it's validati
ng, but we want a set for final evaluation, too.
X_train_transformed, y_train_transformed, X_test_tra
nsformed = process_courses(X_train, y_train, X_test)
```

Logistic Regression

In [11]:

```
model = pickle.load(open('../models/LRmodel2.pkl','r
b'))
```

```
print('Model Hyperparamters:')
print(model)
scores = course_cross_validate(model, X_train, y_tra
in, cv=cv, scoring='accuracy', random_state=111)
print('Validation scores across folds are:')
print(scores)
print('Mean validation scores is:')
print(np.mean(scores))
model.fit(X_train_transformed, y_train_transformed)
y_pred = model.predict(X_test_transformed)
print('Evaluation on hold-out set.')
print(classification_report(y_test, y_pred))
plot_confusion(y_test, y_pred)
```

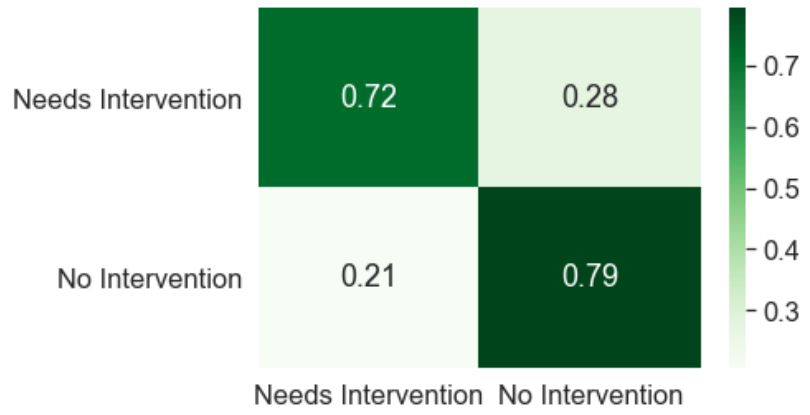
```
Model Hyperparamters:
LogisticRegression(l1_ratio=0.7, penalty='l1', rando
m_state=111,
                   solver='liblinear')
Validation scores across folds are:
[0.7680020947892119, 0.7611940298507462, 0.761917234
1540074, 0.7663698271346254, 0.7723939235201677]
Mean validation scores is:
0.7659754218897517
Evaluation on hold-out set.
                    precision    recall  f1-score
support

Needs Intervention       0.68      0.72      0.70
1804
   No Intervention       0.83      0.79      0.81
2969

          accuracy                           0.77
4773
         macro avg       0.75      0.76      0.76
4773
      weighted avg       0.77      0.77      0.77
4773


Out[11]:

<matplotlib.axes._subplots.AxesSubplot at 0x29c8e776
eb0>
```



The mean cross validated score is similar to the score on the hold

out set, and the confusion matrix is pretty balanced. This is a great start for our model. It successfully classifies about 75% of students. It over-predicts that students will succeed, however.

Decision Tree

I decided to try a decision tree next because I though the data might not be linearly correlated enough for a logistic regression. Perhaps a less linear approach would give us a better accuracy.

In [12]:

```
model = pickle.load(open('../models/DTmodel2.pkl','r
b'))
print('Model Hyperparamters:')
print(model)
scores = course_cross_validate(model, X_train, y_tra
in, cv=cv, scoring='accuracy', random_state=111)
print('Validation scores across folds are:')
print(scores)
print('Mean validation scores is:')
print(np.mean(scores))
model.fit(X_train_transformed, y_train_transformed)
y_pred = model.predict(X_test_transformed)
print('Evaluation on hold-out set.')
print(classification_report(y_test, y_pred))
plot_confusion(y_test, y_pred)
```

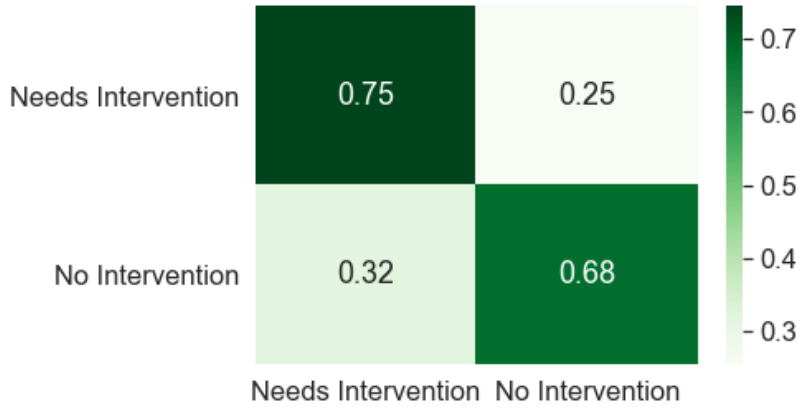
```
Model Hyperparamters:
DecisionTreeClassifier(criterion='entropy', max_dept
h=10, max_features=5,
                       min_samples_split=0.5, random
_state=111,
                       splitter='random')
Validation scores across folds are:
[0.7282010997643362, 0.7389368944749934, 0.755631220
5343112, 0.7569408067050812, 0.7616553169198533]
Mean validation scores is:
0.7482730676797151
Evaluation on hold-out set.
                    precision    recall  f1-score
support

Needs Intervention       0.59      0.75      0.66
1804
   No Intervention       0.82      0.68      0.74
2969

          accuracy                           0.71
4773
         macro avg       0.70      0.71      0.70
4773
      weighted avg       0.73      0.71      0.71
4773

Out[12]:
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x29c83875
520>
```



The decision tree model has lower overall accuracy than the logistic regression. I'm not sure what this means, except that perhaps the division between the classes is actually fairly linear. It is, however better at predicting students who need intervention, improving on the logistic regression accuracy for that class by 4%. It has a more error rate, not preferring one class over another. In this way it performs better.

Random Forest

If one decision tree doesn't work, lets try 150 working together! Maybe they can better classify these students with bootstrap aggregation, or bagging.

In [13]:

```
model = pickle.load(open('../models/RFmodel2.pkl','r
b'))
print('Model Hyperparamters:')
print(model)
scores = course_cross_validate(model, X_train, y_tra
in, cv=cv, scoring='accuracy', random_state=111)
print('Validation scores across folds are:')
print(scores)
print('Mean validation scores is:')
print(np.mean(scores))
model.fit(X_train_transformed, y_train_transformed)
y_pred = model.predict(X_test_transformed)
print('Evaluation on hold-out set.')
print(classification_report(y_test, y_pred))
plot_confusion(y_test, y_pred)
```

```
Model Hyperparamters:
RandomForestClassifier(criterion='entropy', max_dept
h=4, min_samples_split=5,
                       n_estimators=150, n_jobs=-1,
random_state=111)
Validation scores across folds are:
[0.7748101597276774, 0.7708824299554857, 0.778418019
```

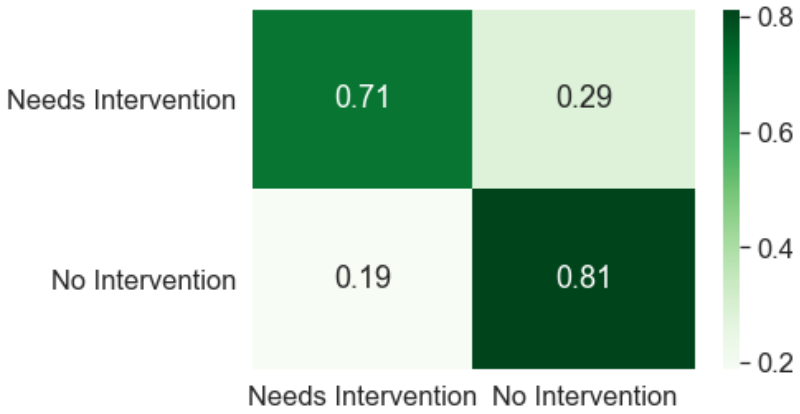
```
9057098, 0.7789418543740179, 0.78627553693033]
Mean validation scores is:
0.7778656001786441
Evaluation on hold-out set.
                    precision    recall  f1-score
support

Needs Intervention       0.70      0.71      0.70
1804
   No Intervention       0.82      0.81      0.82
2969

          accuracy                           0.77
4773
         macro avg       0.76      0.76      0.76
4773
      weighted avg       0.78      0.77      0.77
4773
```

Out[13]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29c8eb17
e50>
```



The random forest ensemble model performs better than the single decision tree, though it introduces a tendency to over-predict 'No Intervention.'

Support Vector Machine (SVM)

This style of model draws a hyperplane between data points, seekign the best fit division between the points. This best fit is defined as the division with the greatest buffer space between the line and one class on one side and the other class on the other. It is an iterative fitting process that stops when it reaches a pre-defined tolerance.

In [ ]:

```
model = pickle.load(open('../models/SVCmodel1.pkl',
'rb'))
print('Model Hyperparamters:')
print(model)
```

```
print(model)
scores = course_cross_validate(model, X_train, y_tra
in, cv=cv, scoring='accuracy', random_state=111)
print('Validation scores across folds are:')
print(scores)
print('Mean validation scores is:')
print(np.mean(scores))
model.fit(X_train_transformed, y_train_transformed)
y_pred = model.predict(X_test_transformed)
print('Evaluation on hold-out set.')
print(classification_report(y_test, y_pred))
plot_confusion(y_test, y_pred, save_path = '../figur
es/SVMconfmatrix.png')
```

eXtreme Gradient Boosting

I tried one tree, I tried a forest of trees, let's try stacking trees on top top of each and letting each one boost the one before it. This is a trendy model these days. Lets see how it performs.

In [6]:

```
model = pickle.load(open('../models/XGBmodel4.pkl',
'rb'))
print('Model Hyperparamters:')
print(model)
scores = course_cross_validate(model, X_train, y_tra
in, cv=cv, scoring='accuracy', random_state=111)
print('Validation scores across folds are:')
print(scores)
print('Mean validation scores is:')
print(np.mean(scores))
model.fit(X_train_transformed, y_train_transformed)
y_pred = model.predict(X_test_transformed)
print('Evaluation on hold-out set.')
print(classification_report(y_test, y_pred))
plot_confusion(y_test, y_pred, save_path = '../figur
es/XGBoost79confmatrix.png')
```

```
Model Hyperparamters:
XGBClassifier(base_score=0.4, booster='gbtree', cols
ample_bylevel=1,
              colsample_bynode=1, colsample_bytree=
0.8, eval_metric='logloss',
              gamma=1, gpu_id=-1, importance_type='g
ain',
              interaction_constraints='', learning_r
ate=0.1, max_delta_step=0,
              max_depth=4, min_child_weight=2, missi
ng=nan,
              monotone_constraints='()', n_estimator
s=200, n_jobs=-1,
              num_parallel_tree=2, random_state=111,
reg_alpha=0, reg_lambda=1,
              scale_pos_weight=1, subsample=0.7, tre
```

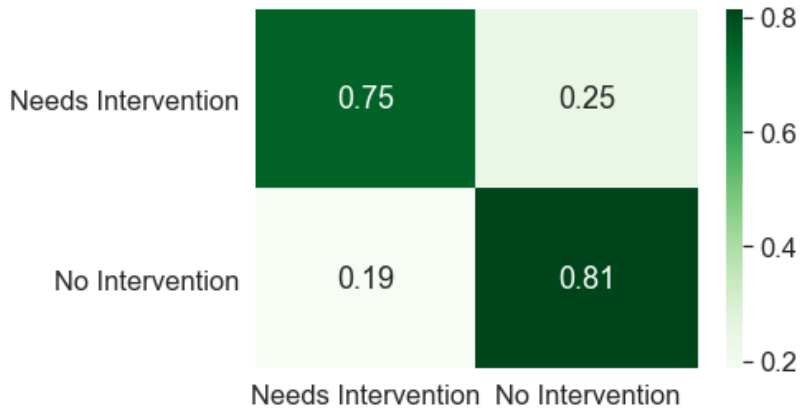
```
e_method='exact',
              validate_parameters=1, verbosity=None)
Validation scores across folds are:
[0.7858078030898141, 0.7873788949986907, 0.785751702
462022, 0.7912519643792562, 0.7980618124672604]
Mean validation scores is:
0.7896504354794087
Evaluation on hold-out set.
                    precision    recall  f1-score
support

Needs Intervention       0.71      0.75      0.73
1804
   No Intervention       0.85      0.81      0.83
2969

          accuracy                           0.79
4773
         macro avg       0.78      0.78      0.78
4773
      weighted avg       0.79      0.79      0.79
4773


Out[6]:

<matplotlib.axes._subplots.AxesSubplot at 0x27e00e54
a60>
```



XGBoost proves itself again! It performs better on both classes and achieves 79% overall accuracy on the hold-out dataset. The validation folds are all in line with the final results, showing it has avoided overfitting problems.

Final model: XGBoost!

While the model accuracies are not that different, the eXtreme Gradient Boost model worked the best over all, with high accuracy and only a small amount of class bias toward 'No Intervention'.

Evaluation:

I would like to dive deeper into the assumptions this model makes and where it does well or poorly. First let's see what the model based it's predictions on. The numbers below are how many times a dataset is split by a given variable, giving a rough indication of which variables are most heavily relied on by the model to classify observations in prediction.

In [50]:

```
from xgboost import plot_importance
model = pickle.load(open('../models/XGBmodel4.pkl',
'rb'))
plt.figure(figsize = (10,7))
ax = plt.subplot()
plot_importance(model, ax=ax)
plt.tight_layout()
plt.savefig('../figures/XGB_final_model_feature_impo
rtance.png', dpi=100)
```

This seems to confirm what our correlation matrix told us. Assessment scores are the best predictor, followed by number of separate days studied and number of assessments taken. The biggest difference is that this model put less emphasis on activities engaged than was suggest by the correlation matrix and more on total_clicks. However, all five of the assessment and interaction statistics rate highly, with previous attempts being lowest, but predictive. The vast majority of students were taking the classes for the first time anyway. Let's take a closer look at the means of these variables for all students in the test set, these