Sami Jawhar - Project 5 - Customer Cancellation Predictor

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1 Definition

1.1 Project Overview and Problem Statement

For a subscription-based business, reducing customer churn is critical to maintaining high growth. This project will examine a nearly six month slice of subscription transactions from such a business in an attempt to identify patterns leading to cancellation. The goal is to train a classifier capable of identifying customers at risk of cancellation using details of upcoming subscription transactions.

The search for a reasonable predictor will follow this general outline: 1. Data preparation * Data visualization * Algorithm selection * Feature preprocessing 1. Imputation of missing values * Creation of dummy columns for categorical features * Benchmarking * Algorithm parameter tuning * Validation testing

The target column, `ServiceLevelChange`, can be one of `No change`, `Downgraded`, or `Deactivated` and represents the service level change of the kit in the 45 days following the refill. As such, this is a multiclass classification problem. Moreover, as will be explored below, the classes are heavily unbalanced with nearly 98% of the samples belonging to the `No change` class. The choice of performance metric will therefore be critical, as many common metrics perform poorly with unbalanced classes. Finally, due to data integrity issues, purchase information is not available for many kits and will need to be imputed.

A note on vocabulary: A customer of this business purchases a **kit** containing several different products. Each of these products are then **refilled** before expiration as part of the subscription service. Samples with a label of `Downgraded` or `Deactivated` will often be referred to below as **at risk**, as predictions of these labels indicate the customer is at risk of cancelling.

1.2 Metrics

Considering that this predictor will be used in an intervention system, it's important to maintain a high precision and minimize false positives. Otherwise, time and money will be spent "intervening" with customers who have no intention of cancelling. Of course, the predictor should catch as many potential cancellations as possible, but the algorithm's performance in this respect can be improved iteratively as customer behavior is better understood. A custom scorer will therefore be used that is the recall score if precision is at least 0.9. Otherwise, the score will be zero.

For example, consider a model that gives a recall of 0.85 and a precision of 0.25. With a recall of 0.85, it might seem that this model is performing well as only 15% of cancellations or downgrades are not being caught by the predictor. However, a precision of 0.25 means that only 25% of the samples are at risk that are predicted as cancellations or downgrades. In other words, there are twice three times as many false positives as there are true positives. The score of this model will be zero, since the precision is less than 0.9.

Consider another model that gives a recall of 0.1 and a precision of 0.95. Only five percent of the samples predicted to be at risk are false positives. Though fewer of the total cancellations are caught, those that are marked as downgrades or cancellations can be trusted to be so. The score of this model would be 0.1, and so it would be preferred over the previous example.

See the Improvement section of the Conclusion for a potential performance metric based on lifetime customer value.

2 Analysis

2.1 Data Exploration

Data for this project was prepared through a deep-dive of the company's database. After identifying several restrcitions - chief among these being lack of audits on the statuses of kits and data integrity issues for older kits - the following features for each refill were identified, organized into views, and extracted: 1. `RefillNumber`: The ordinality of this transaction in the refill history. For example, `RefillNumber=1` corresponds to a kit's first refill, and the fifth refill will have a `RefillNumber` of 5. * `RefillAmount`: The cost of this refill. * `AdvancedNotified`: Customers with up-to-date contact information are sent an email 2-4 weeks before their refill is scheduled for delivery. This field indicates which refills were preceded by such a notification. * `KitType`: A kit's type determines the mix of products contained within it. * `KitPurchasePrice`: The purchase price of the kit. * `KitDistributionChannel`: The distribution channel through which the customer purchased the kit. One of `DIRECT`, `DEALER`, or `WEB`. * `CustomerIsCorporate`: Some customers are associate with each other through a larger organization known as a corporation. * `PreviousRefillsAmount`: The sum of the cost of all previous refills for this kit. * `DaysSinceLastRefill`: The number of days since the last refill. * `DaysSinceKitPurchase`: The number of days since the kit was purchased.

After some initial training and testing, two more features were later added: * `RefillItems`: The number of items in this refill. * `CustomerState`: The US state to which the customer belongs.

```
In [1]: # Import refill data
        import numpy as np
        import pandas as pd
        from IPython.display import display
        refill_data = pd.read_csv('refill_data.csv')
        category_columns = [
            'AdvancedNotified',
            'KitType',
            'KitDistributionChannel',
            'CustomerIsCorporate',
            'CustomerState',
            'ServiceLevelChange'
        ]
        for column in category_columns:
            refill_data[column] = refill_data[column].astype('object')
        display(refill_data.head(3))
        display(refill_data.describe())
        display(refill_data[category_columns].describe())

   RefillNumber  RefillAmount  RefillItems AdvancedNotified KitType  \
0            19        129.40            3                0       G
1            19        129.40            3                0       G
2             1         91.28            7                0       F

   KitPurchasePrice KitDistributionChannel CustomerIsCorporate CustomerState  \
0               NaN                    NaN                   0            NJ
1               NaN                    NaN                   0            CA
2               NaN                    NaN                   0            CA

   PreviousRefillsAmount  DaysSinceLastRefill  DaysSinceKitPurchase  \
0                3689.04                  156                  3145
1                3689.04                  156                  3167
2                   0.00                  NaN                  3185

  ServiceLevelChange
0          No change
1          No change
2          No change


       RefillNumber  RefillAmount   RefillItems  KitPurchasePrice  \
count  47489.000000   47489.00000  47489.000000      35154.000000
mean       8.759523     223.64987      3.677209        376.467484
std        5.656329     164.72680      2.094210        315.602269
min        1.000000      29.45000      1.000000          0.000000
25%        4.000000      75.50000      2.000000        120.800000
50%        8.000000     142.06000      3.000000        333.350000
75%       12.000000     322.61000      5.000000        532.100000
max       31.000000    1194.06000     33.000000       3144.950000

       PreviousRefillsAmount  DaysSinceLastRefill  DaysSinceKitPurchase
count           47489.000000         44431.000000          47489.000000
mean             1686.721326           119.733497           1914.036303
std              1131.503088           105.596982           1809.179766
min                 0.000000             0.000000              0.000000
25%               705.380000            63.000000            943.000000
50%              1691.210000            99.000000           1412.000000
75%              2354.540000           154.000000           1945.000000
max              7272.910000          2872.000000          42464.000000


        AdvancedNotified KitType KitDistributionChannel  CustomerIsCorporate  \
count              47489   47489                  35154                47489
unique                 2      20                      3                    2
```

```
top                          0        J                    DIRECT                     0
freq                     25468    22242                     27530                 41276

       CustomerState  ServiceLevelChange
count          47489               47489
unique            57                   3
top               CA           No change
freq            8927               46412
```

```
In [2]: # Separate data into features (X) and target (y)
        X_raw = refill_data[list(refill_data.columns[:-1])]
        y_all = refill_data[refill_data.columns[-1]]
        print X_raw.shape
        print y_all.shape
```

```
(47489, 12)
(47489,)
```

By looking at the `count` field in the tables above, it is clear that two features (`KitPurchasePrice` and `KitDistributionChannel`) are missing values for 12,335 samples, or 26% of the dataset. This is due to aforementioned data integrity issues in the purchase records of older kits. It might seem that `DaysSinceLastRefill` is also missing values since the value of `count` is less than the total number of samples. However, this is because samples corresponding to first-time refills have no previous refill and so have no valid value for this field. This field will therefore need to be transformed in some way, which is discussed in Data Preprocessing below.

For details of the features' distributions, please refer to the Exploratory Visualization section below.

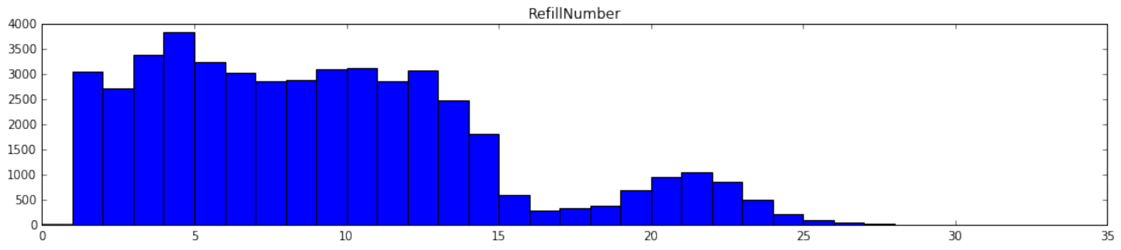
```
In [3]: # Investigate problem severity
        from IPython.display import display
        print "Total refills: {}".format(y_all.count())
        print "Service level changes within 45 days of refill:"
        class_count = pd.DataFrame({
            'samples': y_all.value_counts(),
            'percentage': 100*y_all.value_counts()/y_all.count()
        })
        display(class_count)
```

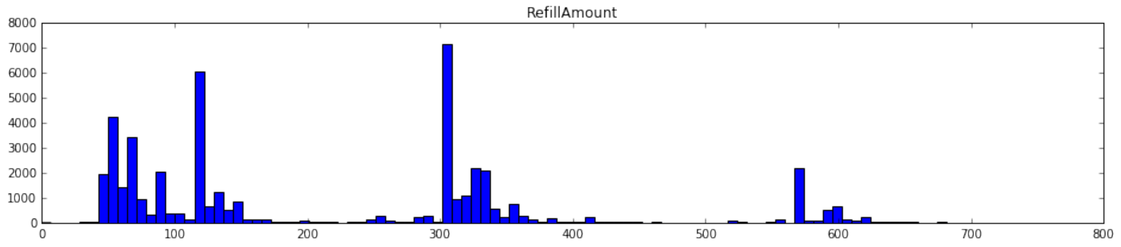
```
Total refills: 47489
Service level changes within 45 days of refill:


             percentage  samples
No change     97.732106    46412
Downgraded     1.981512      941
Deactivated    0.286382      136
```

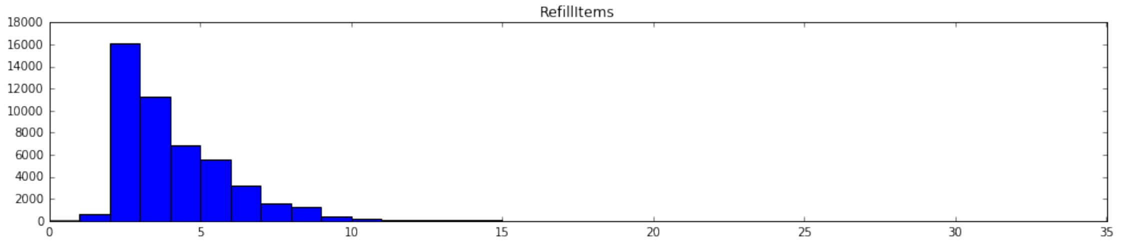
As was mentioned above, the classes are heavily unbalanced, with over 97.7% of the dataset having a label of `No change`. Of the at risk samples, there are almost seven times as many downgrades as there are cancellations. This most likely is due to the company's current retention strategies. As a result, true cancellations represent less than 0.3% of the dataset. It is vital, then, that the dataset be large enough to represent this distribution accurately. Luckily, that is not an issue in this case. Nearly 50,000 samples are available for this project, and more become available every day as the business continues its service.

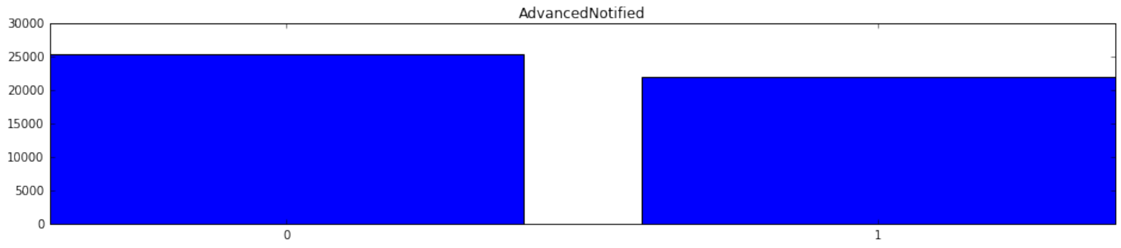
2.2 Exploratory Visualization

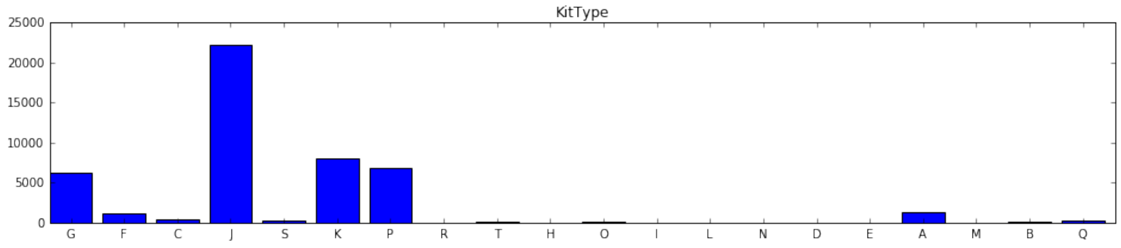
```
In [4]: import matplotlib.pyplot as plt
        %matplotlib inline
        for col, col_data in X_raw.iteritems():
            plt.figure(figsize=(16,3))
            if col in category_columns:
                values = [x for x in col_data.unique() if x == x]
                index = np.arange(len(values))
                counts = list(col_data[col_data == value].count() for value in valu
                bar_width = 0.8

                plt.bar(index, counts, bar_width)
                plt.xticks(index + bar_width/2, values)
            else:
                bins = range(col_data.max() + 1) if len(col_data.unique()) < 100 el
                plot_data = [x for x in col_data.values if not np.isnan(x)]
                plt.hist(
                    plot_data,
                    bins=bins,
                    range=[0, min(col_data.max(), col_data.mean() + 3*col_data.std
                )
            plt.title(col)
            plt.show()
```

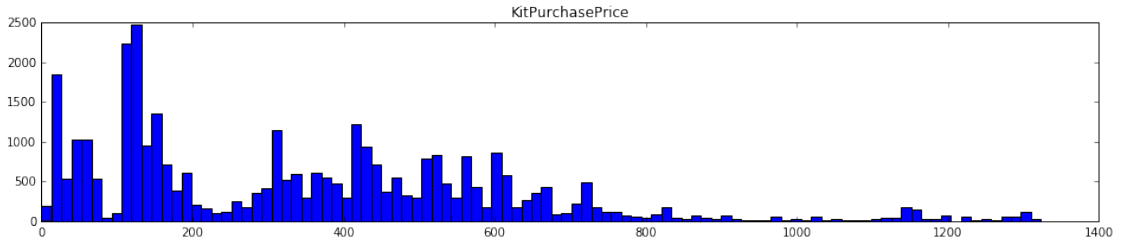


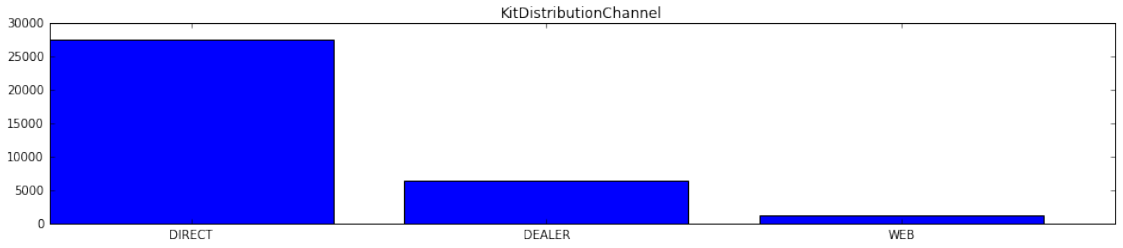

RefillAmount
0
1000
2000
3000
4000
5000
6000
7000
8000
0
100
200
300
400
500
600
700
800

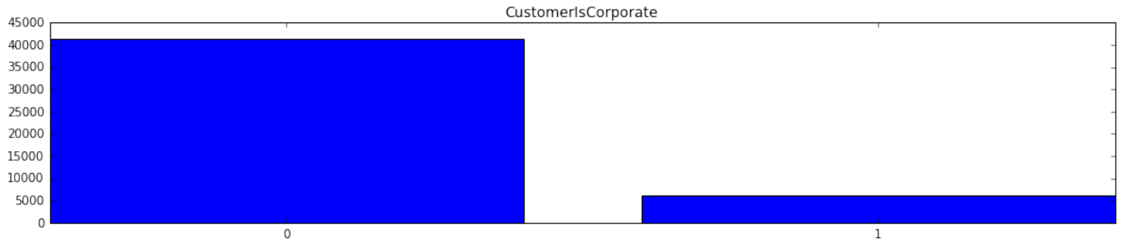

RefillItems
0
2000
4000
6000
8000
10000
12000
14000
16000
18000
0
5
10
15
20
25
30
35

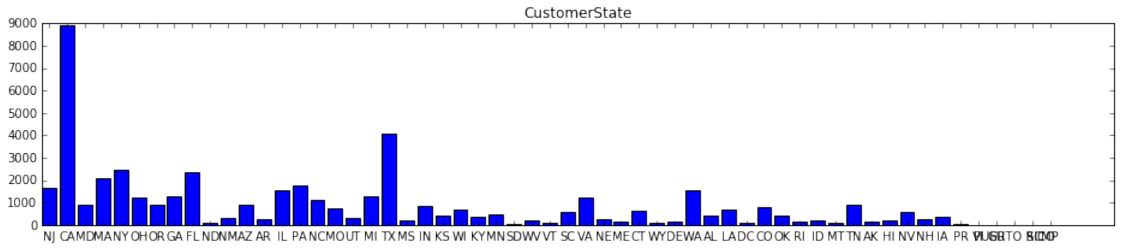

AdvancedNotified
0
5000
10000
15000
20000
25000
30000
0
1

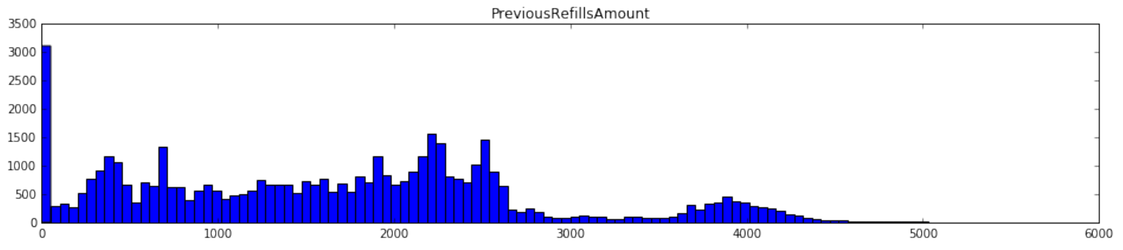

KitType
0
5000
10000
15000
20000
25000
G
F
C
J
S
K
P
R
T
H
O
I
L
N
D
E
A
M
B
Q

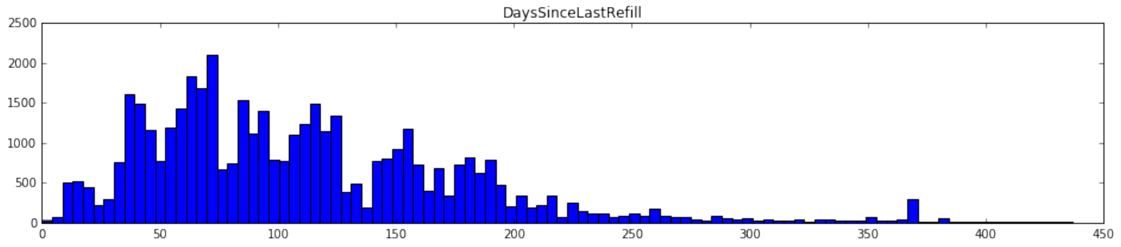

KitPurchasePrice
0
500
1000
1500
2000
2500
0
200
400
600
800
1000
1200
1400

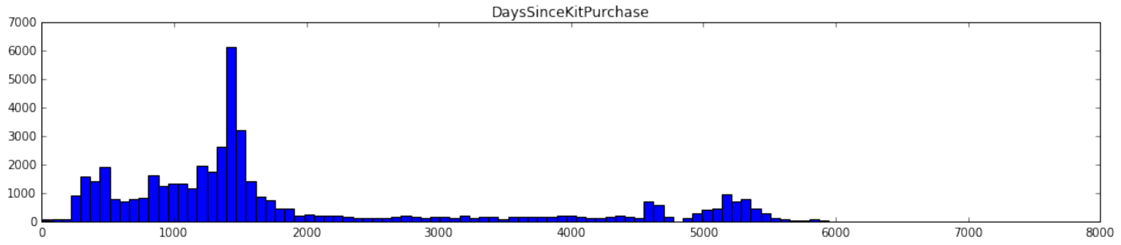

KitDistributionChannel
30000
25000
20000
15000
10000
5000
0
DIRECT
DEALER
WEB


CustomerIsCorporate
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
0
1


CustomerState
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
NJ CA MD MA NY OH OR GA FL ND NM AZ AR IL PA NC MO UT MI TX MS IN KS WI KY MN SD WV VT SC VA NE ME CT WY DE WA AL LA DC CO OK RI ID MT TN AK HI NV NH IA PR


PreviousRefillsAmount
3500
3000
2500
2000
1500
1000
500
0
0
1000
2000
3000
4000
5000
6000





`RefillNumber` is fairly evenly distributed at the lower end, with between 6% and 8% of the samples belonging to each `RefillNumber` value up to 12, after which it drops off sharply. `PreviousRefillsAmount` shares a similar distribution, dropping off after around $2,500, which indicates a fairly consistent refill price. This is confirmed by examining the distribution of `RefillAmount`, which is heavily concentrated around $100, $300, and $550. Also very consistent is the number of items contained in the refill, with nearly all of the samples having a `RefillItems` value between 2 and 6.

The distributions of `RefillNumber`, `PreviousRefillsAmount`, and `DaysSinceKitPurchase` seem to indicate that there are two distinct kit groups. Most of the samples belong to kits sold in the past few years. However, there is also a smaller group of long-standing installs. The behavior of these two groups might differ significantly.

Other notes: * `DaysSinceLastRefill` seems almost normally distributed around 60 days, though it is definitely skewed to the right. * In contrast, `DaysSinceKitPurchase` is heavily concentrated around 1,500 days. * Around half of the refills were preceded by a notification. * Around 60% of the refills belong to kits that were sold directly to the customer. * Almost half of the samples belong to `KitType` J, and nearly all of the samples belong to `KitType` G, J, K, or P. * Over one-fifth of the samples belong to customers in California, with Texas coming in second place at around one-tenth. The other states are relatively evenly distributed.

2.3 Algorithms and Techniques

Scalability is the name of the game, here. With nearly 48,000 samples on which to train, and more assuredly available in a production environment, the algorithm chosen must scale well in the number of samples. In addition, the algorithm must scale well in the number of features. We've identified 10 features to start with but that might, and probably will, grow quickly as the understanding of customer behavior improves. The number of features will likely never outgrow the number of samples, however.

The final model will be used to predict the result of upcoming refills on demand. A quick prediction time is therefore very important, and will it will only become more important as the customer base grows. Lazy learners would therefore not be suitable for this problem. On the other hand, training time is not a significant factor. As new data becomes available, the model can be retrained asynchronously and pushed to live when ready. Online learners would be ideal in this situation, as the true results of each refill are available after 45 days and the model could then be updated with the new information.

Based on the above, and by consulting the sklearn documentation on choosing an estimator, the following algorithms will be trained and tested: * SGD Classifier * Decision Trees (including random forest)

These two classifiers are discussed in more detail below:

2.3.1 Decision Trees

A decision tree classifier immediately stood out to me as a worthy candidate for this situation. Decision trees are used in data mining as they are performant, scalable, and suited to both numerical and categorical data while requiring little data preparation. Perhaps most important when considering that this model must be applied in a non-technical environment, decision trees can be visualized and explained to the layman. A customer retention system would be much more effective it can be intuitively understood by the marketing and rention personnel responsible for its implementation.

2.3.2 Stochastic Gradient Descent

Stochastic gradient descent (SGD) is not a model itself but rather a method of training models such as support vector machines (SVMs) and logistic regression models. Specifically, SGD is a method of finding the minima/maxima of a function by iteratively sweeping over randomly sampled subsets of the training set. It's often used for training neural nets, but those models will not be used in this project due to technical and experiential limitations. Instead, the loss functions made available by sklearn (linear SVMs, logistic regression, perceptron, and others) will be tested. The big benefit of SGD for this project is that it allows for online learning, meaning new results can more easily be incorporated into the model without having to retrain on the entire dataset.

2.4 Benchmark

The business's assumption up to this point was that customers have not been properly educated of the refill process and were cancelling after receiving their first refill. Another assumption was that a few, high-priced items were responsible for a large proportion of the cancellations. These two assumptions together will define our benchmark, which will be as follows: if a refill is the kit's first, assume deactivation. If the average item price in the refill is more than $200, assume deactivation. Otherwise, assume no change. For simplicity, the benchmark will be established as a binary classifier.

3 Methodology

3.1 Data Preprocessing

The following tasks need to be performed: 1. Impute missing values * To increase the predictor's accuracy, samples will be grouped by class before imputing. * First refills have a `NaN` value for `DaysSinceLastRefill`, which would be replaced with the mean during imputation. It would be more appropriate to transform the feature to its reciprocal and give first refills a value of zero. * One-hot encode categorical features * One-hot encoding converts a single categorical feature into multiple binary features, where each binary feature represents a possible value of the original categorical feature. For example, `KitDistributionChannel` has three values: Direct, Dealer, and Web. This feature will be converted to three features: `KitDistributionChannel_Direct`, `KitDistributionChannel_Dealer`, `KitDistributionChannel_Web`. If the original value of `KitDistributionChannel` was Direct, then that corresponding binary feature would have a value of 1 and the others 0. * This is necessary as not all algorithms work well (or at all) with categorical features. One-hot encoding allows these categorical features to be represented simply as vectors (e.g. [1,0,0] above), which is much easier to work with.

3.2 Implementation

3.2.1 Imputing and One-hot Encoding

```
In [7]: # Impute missing values by class
        X_imputed = pd.DataFrame()
        results = y_all.unique()
        for result in results:
            X_class = X_raw[y_all == result]
            X_class_imputed = pd.DataFrame(index = X_class.index)
            for col, col_data in X_class.iteritems():
                # Impute categorical with mode, numerical with mean
                fill_value = col_data.mode()[0] if col_data.dtype == object else co
                X_class_imputed = X_class_imputed.join(col_data.fillna(fill_value))
            X_imputed = X_imputed.append(X_class_imputed, verify_integrity = True)
        X_imputed.sort_index(inplace=True)

        X_all = pd.DataFrame(index = X_imputed.index)
        for col, col_data in X_imputed.iteritems():
            # Transform DaysSinceLastRefill to reciprocal, fill NULL with 0
            if col == 'DaysSinceLastRefill':
                col_data = X_raw[col].rtruediv(1).replace(np.inf, 0).fillna(0)
                col_data.name = 'RefillFrequency'
            # Split categorical features into multiple binary columns
            elif col_data.dtype == object and set(col_data.unique()) != set([0,1]):
                col_data = pd.get_dummies(col_data, prefix=col)
            X_all = X_all.join(col_data)

        display(X_all.head())
```

```
   RefillNumber  RefillAmount  RefillItems  AdvancedNotified  KitType_A  \
0             19        129.40            3                0            0
1             19        129.40            3                0            0
2              1         91.28            7                0            0
3              2        115.45            2                0            0
4              8        320.50            8                0            0

   KitType_B  KitType_C  KitType_D  KitType_E  KitType_F  \
0          0          0          0          0          0
1          0          0          0          0          0
2          0          0          0          0          1
3          0          0          0          0          1
4          0          1          0          0          0

           ...             CustomerState_VA  CustomerState_VI  CustomerState_VT  \
0          ...                            0                 0                 0
1          ...                            0                 0                 0
2          ...                            0                 0                 0
3          ...                            0                 0                 0
4          ...                            0                 0                 0

   CustomerState_WA  CustomerState_WI  CustomerState_WV  CustomerState_WY  \
0                 0                 0                 0                 0
1                 0                 0                 0                 0
2                 0                 0                 0                 0
3                 0                 0                 0                 0
4                 0                 0                 0                 0

   PreviousRefillsAmount  RefillFrequency  DaysSinceKitPurchase
0                3689.04         0.006410                  3145
1                3689.04         0.006410                  3167
2                   0.00         0.000000                  3185
3                  91.28         0.026316                  3223
4                1498.30         0.002695                  5190

[5 rows x 89 columns]
```

3.2.2 Performance Metric Definition

As discussed above, we will be using a custom metric that takes into account both precision and recall in the following way: * If the precision is less than 0.9, the score is zero * Otherwise, the score is the recall score

```
In [10]: from sklearn.metrics import recall_score, precision_score, make_scorer
         labels = ['Deactivated', 'Downgraded']

         def scoring_function(y_true, y_pred):
             precision = precision_score(y_true, y_pred, labels=labels, average='mi
             if precision < 0.9:
                 return 0
             return recall_score(y_true, y_pred, labels=labels, average='micro')

         scorer = make_scorer(scoring_function)
         recall_scorer = make_scorer(recall_score, labels=labels, average='micro')
         precision_scorer = make_scorer(precision_score, labels=labels, average='mi
```

3.2.3 Benchmarking and Initial Algorithm Testing

Before training can begin, the data must be split into training and testing sets composing 80% and 20% of the total dataset, respectively. The testing set will be reserved for validating the final, tuned model. In this way, we can avoid overfitting and ensure that the final model generalizes well to unseen data.

During training, the performance of each algorithm will be tested using cross-validation. The process of cross-validation is as follows: 1. The training set is partitioned into a number of smaller subsets or "folds" (three, in this case) 2. One of the folds is reserved as the testing fold 3. The model is trained on the non-reserved folds 4. The model's performance is tested on the reserved testing fold 5. Steps 2-4 are repeated until each fold has been used as the testing fold exactly once 6. The performance of the model is taken as the average of its performance in each of the above iterations

Cross-validation maximizes the amount of data available for training while ensuring the model is still tested against unseen data, which is critical to any performance measurement.

In both the train/test split and cross-validation outlined above, the distribution of the classes will be preserved by ensuring that, after each split, the resulting subsamples have the same class distribution as the dataset as a whole. This is especially important, given the heavily unbalanced dataset.

As discussed above, we will be testing `SGDClassifier`, `DecisionTreeClassifier`, and `RandomForestClassifier`. in addition to the benchmark. All parameters for the classifiers will be left at default values, as a parameter grid search will be conducted later on to find the optimum values. This initial test will validate the data preprocessing performed above and allow for comparing the initial, untuned performance of the algorithms.

```
In [11]: from sklearn.linear_model import SGDClassifier
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.cross_validation import train_test_split, cross_val_score

         # Prepare candidate algorithms
         random_state = 1993
         results = []
         classifiers = [
             DecisionTreeClassifier(random_state=random_state),
             RandomForestClassifier(random_state=random_state),
             SGDClassifier(random_state=random_state)
         ]
         X_train, X_test, y_train, y_test = train_test_split(
             X_all,
             y_all,
             test_size=0.2,
             stratify=y_all,
             random_state=random_state
         )

         # Establish benchmark
         y_bench = []
         for index, row in X_train.iterrows():
             if row['RefillNumber'] == 1:
                 y_bench.append(1)
             elif row['RefillAmount']/row['RefillItems'] >= 200:
                 y_bench.append(1)
             else:
                 y_bench.append(0)
         y_bench = pd.Series(y_bench)
         y_true = 1 - pd.get_dummies(y_train)['No change']
         results.append([
             'Benchmark',
             recall_score(y_true, y_bench),
             precision_score(y_true, y_bench)
         ])

         # Test candidate algorithms
         for clf in classifiers:
             classifier = clf.__class__.__name__
             recall = cross_val_score(clf, X_train, y_train, scoring=recall_scorer,
             precision = cross_val_score(clf, X_train, y_train, scoring=precision_s
             results.append([classifier, recall.mean(), precision.mean()])

         results = pd.DataFrame(
             data = results,
             columns = [
                 'classifier',
                 'recall',
                 'precision'
             ]
         )

         display(results)
```

```
               classifier    recall  precision
0               Benchmark  0.274942   0.086307
1  DecisionTreeClassifier  0.223924   0.187479
2  RandomForestClassifier  0.134582   0.469418
3           SGDClassifier  0.015099   0.037342
```

The benchmark model is clearly lacking. Though it catches more cancellations (27.5%) than any of the other algorithms, it also has the second to lowest precision of the lot. On the other hand, the random forest has the second to lowest recall but the highest precision. `SGDClassifier` has the lowest performance in both metrics. I'm interested to see how this changes after further tuning.

3.2.4 Parameter Tuning

Each algorithms takes a number of parameters as inputs. These parameters can drastically affect the performance of the algorithm. In the case of SGD, different values of the `loss` parameter correspond to completely different models. Unfortunately, the highest-performing combination of parameters cannot be determined *a priori* but rather must simply be tested. This process is called parameter tuning.

One can imagine each possible combination of parameters as a cell in an n-dimensional grid, where n corresponds to the number of parameters being tuned. This grid is then exhaustively searched for the "best" parameter values, where the performance of each cell is tested using cross-validation (as outlined above). The highest-performing parameter values are then reported, along with their score.

For the decision tree and random forest classifiers, the following parameters are tuned: * `criterion`: the metric of information gain used at each step in the decision tree * `max_features`: the number of features considered at each step in the tree when evaluating which feature best partitions the data, according the metric defined by the `criterion` parameter * `max_depth`: the maximum depth of the tuned tree. Decision trees have a tendency to overfit, so deeper is not always better. * `min_samples_split`: the minimum number of samples needed in order to consider adding another split to the tree.

One addition parameter is tuned for `RandomForestClassifier`: * `n_estimators`: the number of decision trees to train, the combination of which compose the *random forest*

```
In [8]: from sklearn.grid_search import GridSearchCV
        from sklearn.tree import DecisionTreeClassifier
        parameters = [
            {
                'criterion': ('gini', 'entropy'),
                'max_features': ('sqrt', 'log2', None),
                'max_depth': (3, 4, 5, 6, 7, 8, 9, 10, None),
                'min_samples_split': (2, 5, 10, 25, 50, 75, 100, 150, 200, 250, 500
            }
        ]
        clf = GridSearchCV(DecisionTreeClassifier(random_state=random_state), param
        clf.fit(X_train, y_train)
        print "Best DecisionTreeClassifier score: {}".format(clf.best_score_)
        print clf.best_params_
```

```
Best DecisionTreeClassifier score: 0.113688103654
{'max_features': None, 'min_samples_split': 2, 'criterion': 'entropy', 'max_depth':
```

```
In [9]: from sklearn.grid_search import GridSearchCV
        from sklearn.ensemble import RandomForestClassifier
        parameters = [
            {
```

```
            'n_estimators': (2, 5, 10, 15, 20, 25, 50, 75, 100),
            'criterion': ('gini', 'entropy'),
            'max_features': ('sqrt', 'log2', None),
            'max_depth': (3, 4, 5, 6, 7, 8, 9, 10, None),
            'min_samples_split': (2, 5, 10, 25, 50, 75, 100, 150, 200, 250, 50(
        }
    ]
    clf = GridSearchCV(RandomForestClassifier(random_state=random_state), paran
    clf.fit(X_train, y_train)
    print "Best RandomForestClassifier score: {}".format(clf.best_score_)
    print clf.best_params_
```

```
Best RandomForestClassifier score: 0.155463101231
{'max_features': None, 'min_samples_split': 10, 'criterion': 'entropy', 'max_depth'
```

The following parameters will be tuned for `SGDClassifier`, many of which are discussed in more detail above: * `loss`: as mention above, this corresponds to the loss function or model being trained. * `n_iter`: the number of passes, or iterations, over the training set * `warm_start`: whether or not the result of a previous iteration should be used when initializing the next iteration * `penalty`, `alpha`, and `l1_ratio` are variables in the loss function

```
In [10]: from sklearn.grid_search import GridSearchCV
         from sklearn.linear_model import SGDClassifier
         parameters = [
             {
                 'loss': ('hinge', 'log', 'modified_huber', 'squared_hinge', 'perce
                 'penalty': ('none', 'l2', 'l1', 'elasticnet'),
                 'alpha': (0.0001, 0.001, 0.01),
                 'l1_ratio': (0.0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, 1.(
                 'n_iter': (1, 5, 10, 50, 100),
                 'warm_start': (True, False)
             }
         ]
         clf = GridSearchCV(SGDClassifier(random_state=random_state), parameters, s
         clf.fit(X_train, y_train)
         print "Best SGDClassifier score: {}".format(clf.best_score_)
         print clf.best_params_
```

```
Best SGDClassifier score: 0.00115752926863
{'warm_start': False, 'n_iter': 100, 'loss': 'log', 'l1_ratio': 0.125, 'fit_interce
```

4 Results

4.1 Model Evaluation and Validation

Based on the tuned performance of the models above, `RandomForestClassifier` seems to be a clear winner; in particular, a random forest of 50 decision trees, each of which has no maximum depth but stops splitting once the sample size is less than 10. To confirm these parameters' performance, the model will now be tested against the testing set, which contains as-yet unseen samples.

```
In [13]: from sklearn.tree import DecisionTreeClassifier
         from sklearn.ensemble import RandomForestClassifier
         clf = RandomForestClassifier(
             max_features = None,
             min_samples_split = 10,
             criterion = 'entropy',
             max_depth = None,
             n_estimators = 50,
             random_state=random_state
         )
         clf.fit(X_train, y_train)
         y_pred = clf.predict(X_test)
         recall = recall_score(y_test, y_pred, labels=['Deactivated', 'Downgraded']
         precision = precision_score(y_test, y_pred, labels=['Deactivated', 'Downgr
         print "Test Recall: {}".format(recall)
         print "Test Precision: {}".format(precision)
```

```
Test Recall: 0.162790697674
Test Precision: 0.945945945946
```

This model generalizes well to unseen data. Its performance on the testing set (score of 0.155) is very similar to its performance on the training set (score of 0.163). Even better, its performance is reasonably strong. Its precision is above the required threshold of 0.9, and its recall of 0.163 is more than enough to consider using the model in a test intervention system. Moreover, it is much more accurate than the benchmark. The simple model formed by the assumptions the business had been making only had a recall of 0.274942 and precision of 0.086307. In other words, it predicted more of the cancellations, but it also predicted cancellation far more often than was true.

The benchmark model would be useless in an intervention system as the value recovered from saving potential quits would quickly be burnt pursuing the wrong targets. In contrast, the random forest classifier trained above rarely predicts a cancellation that is unwarranted. However, its clear that some aspect of the problem is still not being captured by the data. I believe that identifying additional relevant features - for example, by conducting exit interviews with customers who cancelled unpredictedly - will improve the recall. In the meantime, I believe that this model can still save a significant number of customers.

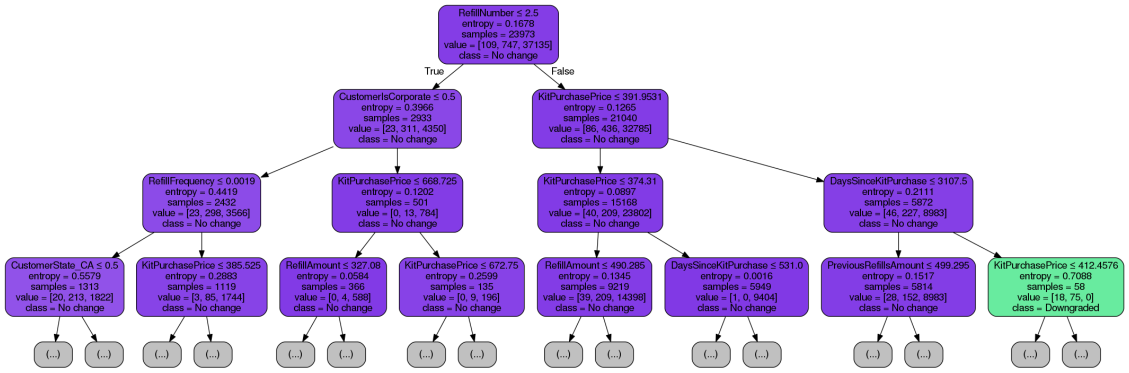
5 Conclusion

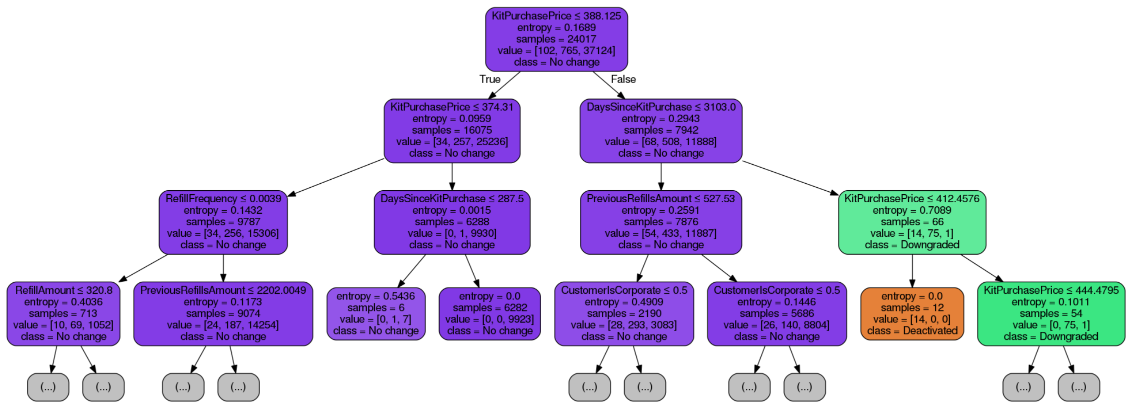
5.1 Free-Form Visualization

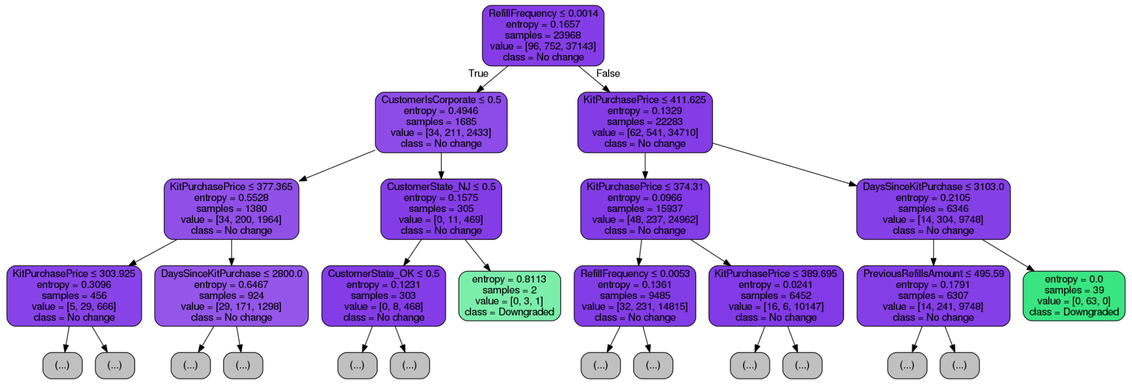
A predictor is useful, but far more useful is intuitive understanding of the problem at hand. It's lucky, then, that the two highest-performing models (the decision tree and, by extension, the random forest) can be represented visually. The behavior of the important features will be explored below.

```
In [12]: relevance = pd.DataFrame([clf.feature_importances_], index=['importance'],
         display(relevance[relevance > 0.01].dropna(axis=1).transpose().sort_values

                         importance
DaysSinceKitPurchase       0.229165
KitPurchasePrice           0.201741
PreviousRefillsAmount      0.100738
RefillFrequency            0.098787
RefillAmount               0.059242
RefillNumber               0.026945
CustomerState_CA           0.022067
RefillItems                0.020982
CustomerIsCorporate        0.014289
CustomerState_NY           0.011180
```

```
In [13]: from sklearn.externals.six import StringIO
         from IPython.display import Image
         from sklearn.tree import export_graphviz
         from pydot import graph_from_dot_data

         for dt in clf.estimators_[:3]:
             dot_data = StringIO()
             export_graphviz(
                 dt,
                 out_file=dot_data,
                 feature_names=X_all.columns,
                 class_names=clf.classes_,
                 max_depth=3,
                 filled=True,
                 rounded=True,
                 special_characters=True
             )
             graph = graph_from_dot_data(dot_data.getvalue())
             display(Image(graph.create_png()))
```


RefillNumber ≤ 2.5 entropy = 0.1678 samples = 23973 value = [109, 747, 37135] class = No change
True
False
CustomerIsCorporate ≤ 0.5 entropy = 0.3966 samples = 2933 value = [23, 311, 4350] class = No change
KitPurchasePrice ≤ 391.9531 entropy = 0.1265 samples = 21040 value = [86, 436, 32785] class = No change
RefillFrequency ≤ 0.0019 entropy = 0.4419 samples = 2432 value = [23, 298, 3566] class = No change
KitPurchasePrice ≤ 668.725 entropy = 0.1202 samples = 501 value = [0, 13, 784] class = No change
KitPurchasePrice ≤ 374.31 entropy = 0.0897 samples = 15168 value = [40, 209, 23802] class = No change
DaysSinceKitPurchase ≤ 3107.5 entropy = 0.2111 samples = 5872 value = [46, 227, 8983] class = No change
CustomerState_CA ≤ 0.5 entropy = 0.5579 samples = 1313 value = [20, 213, 1822] class = No change
KitPurchasePrice ≤ 385.525 entropy = 0.2883 samples = 1119 value = [3, 85, 1744] class = No change
RefillAmount ≤ 327.08 entropy = 0.0584 samples = 366 value = [0, 4, 588] class = No change
KitPurchasePrice ≤ 672.75 entropy = 0.2599 samples = 135 value = [0, 9, 196] class = No change
RefillAmount ≤ 490.285 entropy = 0.1345 samples = 9219 value = [39, 209, 14398] class = No change
DaysSinceKitPurchase ≤ 531.0 entropy = 0.0016 samples = 5949 value = [1, 0, 9404] class = No change
PreviousRefillsAmount ≤ 499.295 entropy = 0.1517 samples = 5814 value = [28, 152, 8983] class = No change
KitPurchasePrice ≤ 412.4576 entropy = 0.7088 samples = 58 value = [18, 75, 0] class = Downgraded
(...)


KitPurchasePrice ≤ 388.125 entropy = 0.1689 samples = 24017 value = [102, 765, 37124] class = No change
True
False
KitPurchasePrice ≤ 374.31 entropy = 0.0959 samples = 16075 value = [34, 257, 25236] class = No change
DaysSinceKitPurchase ≤ 3103.0 entropy = 0.2943 samples = 7942 value = [68, 508, 11888] class = No change
RefillFrequency ≤ 0.0039 entropy = 0.1432 samples = 9787 value = [34, 256, 15306] class = No change
DaysSinceKitPurchase ≤ 287.5 entropy = 0.0015 samples = 6288 value = [0, 1, 9930] class = No change
PreviousRefillsAmount ≤ 527.53 entropy = 0.2591 samples = 7876 value = [54, 433, 11887] class = No change
KitPurchasePrice ≤ 412.4576 entropy = 0.7089 samples = 66 value = [14, 75, 1] class = Downgraded
RefillAmount ≤ 320.8 entropy = 0.4036 samples = 713 value = [10, 69, 1052] class = No change
PreviousRefillsAmount ≤ 2202.0049 entropy = 0.1173 samples = 9074 value = [24, 187, 14254] class = No change
entropy = 0.5436 samples = 6 value = [0, 1, 7] class = No change
entropy = 0.0 samples = 6282 value = [0, 0, 9923] class = No change
CustomerIsCorporate ≤ 0.5 entropy = 0.4909 samples = 2190 value = [28, 293, 3083] class = No change
CustomerIsCorporate ≤ 0.5 entropy = 0.1446 samples = 5686 value = [26, 140, 8804] class = No change
entropy = 0.0 samples = 12 value = [14, 0, 0] class = Deactivated
KitPurchasePrice ≤ 444.4795 entropy = 0.1011 samples = 54 value = [0, 75, 1] class = Downgraded
(...)


RefillFrequency ≤ 0.0014 entropy = 0.1657 samples = 23968 value = [96, 752, 37143] class = No change
True
False
CustomerIsCorporate ≤ 0.5 entropy = 0.4946 samples = 1685 value = [34, 211, 2433] class = No change
KitPurchasePrice ≤ 411.625 entropy = 0.1329 samples = 22283 value = [62, 541, 34710] class = No change
KitPurchasePrice ≤ 377.365 entropy = 0.5528 samples = 1380 value = [34, 200, 1964] class = No change
CustomerState_NJ ≤ 0.5 entropy = 0.1575 samples = 305 value = [0, 11, 469] class = No change
KitPurchasePrice ≤ 374.31 entropy = 0.0966 samples = 15937 value = [48, 237, 24962] class = No change
DaysSinceKitPurchase ≤ 3103.0 entropy = 0.2105 samples = 6346 value = [14, 304, 9748] class = No change
KitPurchasePrice ≤ 303.925 entropy = 0.3096 samples = 456 value = [5, 29, 666] class = No change
DaysSinceKitPurchase ≤ 2800.0 entropy = 0.6467 samples = 924 value = [29, 171, 1298] class = No change
CustomerState_OK ≤ 0.5 entropy = 0.1231 samples = 303 value = [0, 8, 468] class = No change
entropy = 0.8113 samples = 2 value = [0, 3, 1] class = Downgraded
RefillFrequency ≤ 0.0053 entropy = 0.1361 samples = 9485 value = [32, 231, 14815] class = No change
KitPurchasePrice ≤ 389.695 entropy = 0.0241 samples = 6452 value = [16, 6, 10147] class = No change
PreviousRefillsAmount ≤ 495.59 entropy = 0.1791 samples = 6307 value = [14, 241, 9748] class = No change
entropy = 0.0 samples = 39 value = [0, 63, 0] class = Downgraded
(...)

It seems that the predictor has uncovered a pattern of high cancellation among low-priced kits that have been active for a long time. After some consideration, this makes sense. Even highly-satisfied customers will eventually cancel, for example due to a change in circumstance such as retiring. Such customers might neglect to cancel their subscription. Then, after receiving a refill they might not have been expecting, they would have to go through the process of returning the items and cancelling the subscription, all of which involves lost time and money. This predictor would be able to identify such customers and prevent that waste with some effort beforehand.

5.2 Reflection

To recap, the process undertaken in this project: 1. Data preparation: identifying potentially relevant features of each refill, locating and/or calculating these features in the data, and determining the label for each sample * Data visualization: exploring the distribution of the data, both to form a stronger understanding of the relationship between the features and to identify any preprocessing necessary before training * Algorithm selection: taking into account the details of the problem at hand to choose a handful of candidate algorithms for training * Benchmarking: Outlining and testing a benchmark against which the candidate algorithms can be measured * Feature preprocessing: carrying out the preprocessing as identified in the data visualization and exploration stage, including imputing missing values and one-hot encoding categorical features * Algorithm parameter tuning: train/test splitting the data, then performance parameter grid searches with cross-validation to identify the highest-performing model of the candidates * Validation testing: testing the performance of the chosen model against a validation data set

Far and away, the main challenge in this project was in preparing the data. Many new views were prepared involving several tables. For example, the necessary table relationships to uncover purchase information for kits had to be discovered, and these were still not enough to overcome data integrity issues for older kits. These data integrity issues continued to complicate the project beyond the data preparation phase. Missing values for certain features needed to be imputed in the preprocessing phase. On the other hand, there is an abundance of available data. Modeling such an unbalanced problem would be highly innacurate were there not tens of thousands of available samples. Moreover, I have already begun the process of improving data storage protocols, including ensuring that certain historical data is stored to make reporting easier (or, in some cases, simply possible) in the future. This will enable further iterative improvement of the predictor.

Two issues mentioned above impacted the project in both positive and negative ways: the large amount of data and the unbalanced classes. A large dataset is a luxury, but it also led to comparatively long training times. Performing a parameter grid search took upwards of a few hours for the more complicated algorithms, even on a powerful dedicated machine. The unbalanced classes made choosing a performance metric a novel and engaging challenge. However, I suspect they also raise the standard on the input data for producing a high-quality model.

At this point, though, I am quite pleased with the result of this project. For several reasons, not least among them being my own novicehood, I was not expecting the final model to have as high a precision as it does. To be sure, I would prefer that the precision had also exceeded my expectation. All that said, I feel quite comfortable testing this model in a production-like environment.

5.3 Improvement

As I've mentioned above, I believe that adding additional relevant features will improve the recall. In particular, the business believes that certain key, high-priced items are possibly triggering cancellations. I've considered adding a boolean "is_included" feature for each of those items. Also, the data has a focus on kits rather than customers. For example, if a customer were to cancel a kit and purchase a new one, this is not explicitly reflected in the data at the moment. Further, features like customer lifetime and balance due at the time of refill might expose critical patterns in behavior.

Exploring the customer angle further, I've also had the idea to perform a customer segmentation analysis. Such an analysis could provide valuable insight into customer behavior in addition to providing a few relevant features for training the predictor. The first of these would obviously be the segment number of the customer to which the kit belongs. Clustering would also allow me to establish an average customer lifetime value (CLV) for each segment. A cost function for the predictor could then be defined using this CLV in the following way: if the predictor fails to catch a cancellation, it will incur a penalty of the deficit between that customer's current lifetime value and the average CLV for that customer's segment. In this way, the process of fitting the model to the data will be directly optimizing the potential value that could be recovered by using the predictor.

Finally, I will admit to being disappointed that the `SGDClassifier` algorithm did not perform very well. An online learner would be a big bonus for iteratively improving the predictor. One such learner I left out of this project, mostly due to lacking the requisite experience, is a neural net. Though it carries with it the disadvantage of being black boxes, it is an online learner with a strong reputation in the industry today.