Newsletter Churn Prediction

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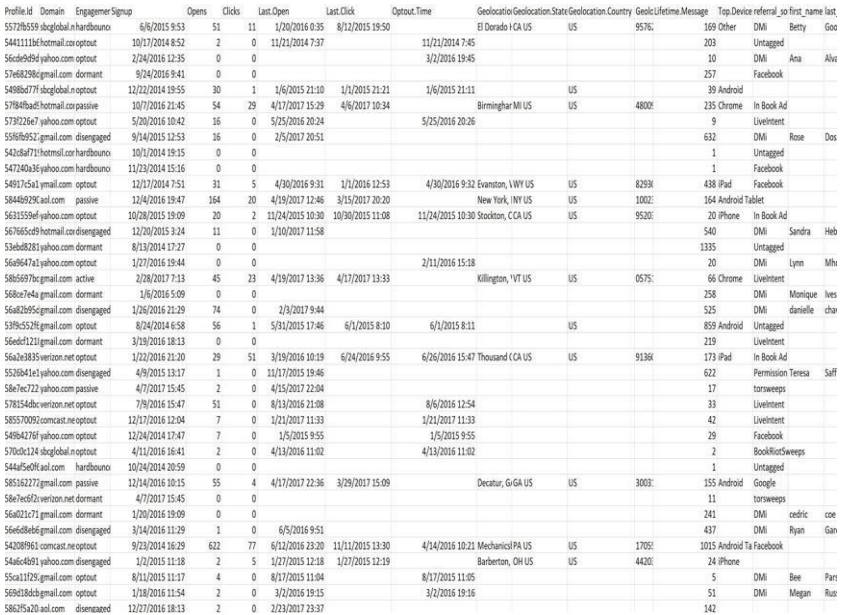
Addressing the Dataset

- Feature extraction and data wrangling to determine relevant features(many features not usable)
- Data is unbalanced, the majority of users were remaining subscribed
- Different data transformations proved to be useful for the different models, as well as different features



Profile.Id	Domain	Engagemer	Signup	Opens	Clicks	Last.Open	Last.Click	Optout.Time	Geolocatio	Geolocation.State	Geolocation.Country	Geolc	Lifetime.Message	Top.Device	referral_so	first_name	last
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56cde9d9d	yahoo.com	optout	2/24/2016 12:35	0	0			3/2/2016 19:45					10	DMI	Ana	Alva	
57e68298c	gmail.com	dormant	9/24/2016 9:41	0	0								257	Facebook			
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57f84fbad	hotmail.co	passive	10/7/2016 21:45	54	29	4/17/2017 15:29	4/6/2017 10:34		Birminghar	MI	US	4800	235	Chrome	In Book Ad		
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55ca11f29	gmail.com	optout	8/11/2015 11:17	4	0	8/17/2015 11:04		8/17/2015 11:05					5	DMI	Bee	Parr	
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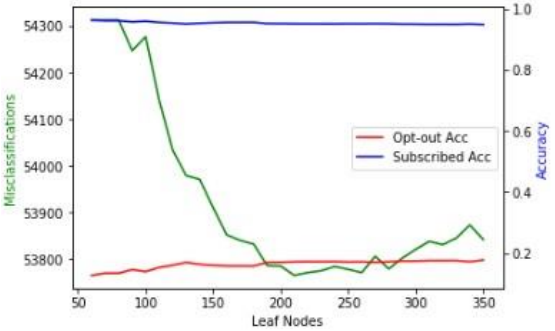
5862f5a20	aol.com	disengaged	12/27/2016 18:13	2	0	2/23/2017 23:37							142				

Decision Tree

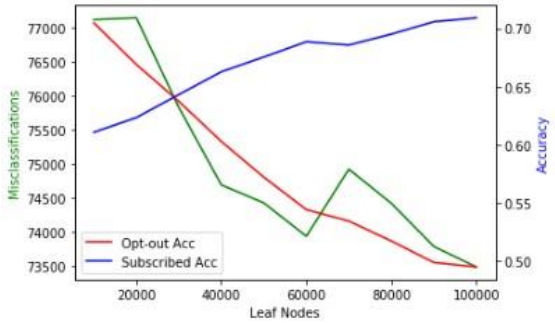
- Used relevant features and got unbalanced results
  - Minimal misclassifications at 210 leaf nodes
  - Great subscriber accuracy with poor opt-out accuracy

```
Test Opt-out Percent Correct:  0.17116292427261143
Test Subscribed Percent Correct:  0.951306222766972
Test Misclassifications:  53765
```



- Class weights of tree were balanced
  - More misclassifications than unbalanced tree
  - Less gap in the accuracy of predicted Opt-out and Subscribed users
  - Misclassifications continue to decrease as max nodes increases

```
Test Opt-out Percent Correct:  0.5440920431497137
Test Subscribed Percent Correct:  0.6885279565683337
Test Misclassifications:  73937
```



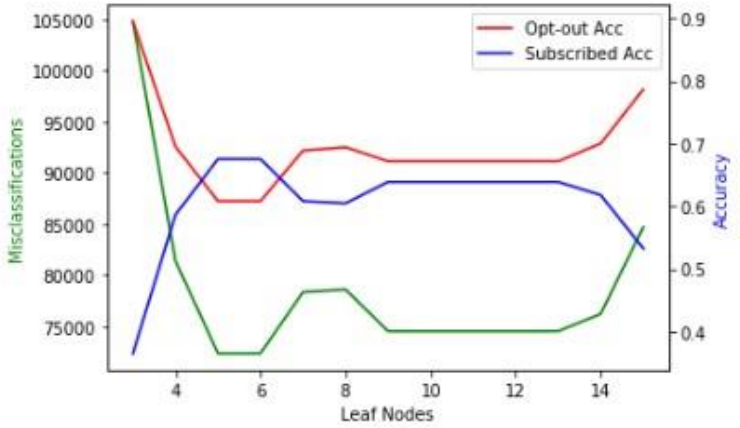
Decision Tree Improvement

Problems:

- Model training time is very high
- Final tree is very complex with no optimal max leaf nodes
- Accuracy of model still suffered

Discovered Solution:

- Initial inclusion of the large amount of one-hot encoded user genre preference features helped lower misclassifications before class weights were balanced
- After balancing the weights these features harmed the accuracy of the model while making the model overly complex
- Removal of preference features greatly simplified model and improved accuracy
- Max leaf nodes was optimized at 5
- A defined max depth only hindered the accuracy
- Other variables such as minimum samples for a split and minimum samples per leaf had no effect on outcome




```
Training Opt-out Percent Correct:  0.609967796350253
Training Subscribed Percent Correct:  0.6751996255300402
Test Opt-out Percent Correct:  0.6083140380162619
Test Subscribed Percent Correct:  0.6755331095866676
Test Misclassifications:  72384
```

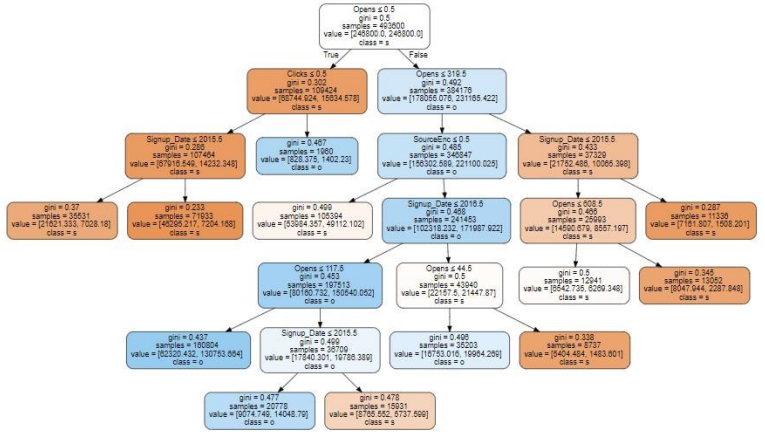
Decision Tree Conclusion

If the goal was to minimize misclassifications:

- Balancing the class weights would hurt the results
- Subscriber prediction accuracy excels at the cost of the opt-out accuracy

With a goal of predicting users who will potentially opt-out:

- Balancing class weights puts an emphasis on equal accuracy for classification
- More useful outcome since the model attempts to accurately predict opt-out users

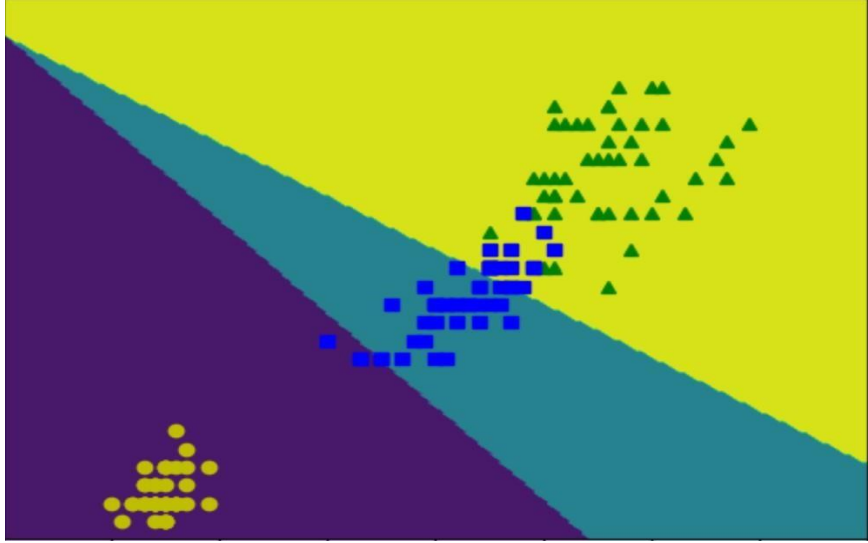


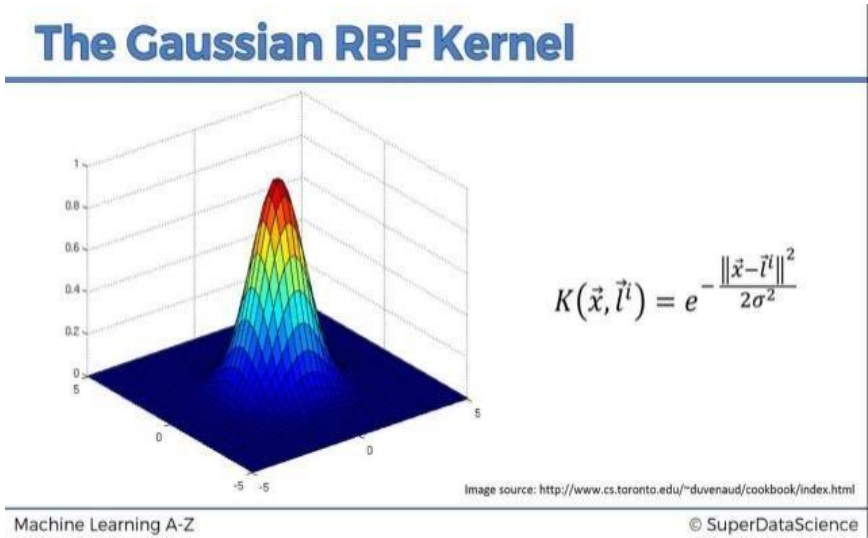
Takeaways:

- An overly complex model will lead to little information gain with each split
- Even after all attempted optimization, a decision tree is most likely the ideal model for the task

SVM

- Standard SVC from scikit-learn too slow, hard to test with multiple parameters due to long training times
- Used LinearSVC, got imbalanced results(very low accuracy for predicting optouts, and very high accuracy for predicting subscribers)
- Used Nystroem kernel approximation paired with a LinearSVC, and RBFSampler kernel approximation paired with SGDClassifier; results were still not good
- The above 2 models behave similar to an SVM with an RBF kernel, but with much faster training times
- Attempted an ensemble of all the above models using a VotingClassifier ;no improvement
- Attempted to loop through all possible parameters for most of the above models; no improvement



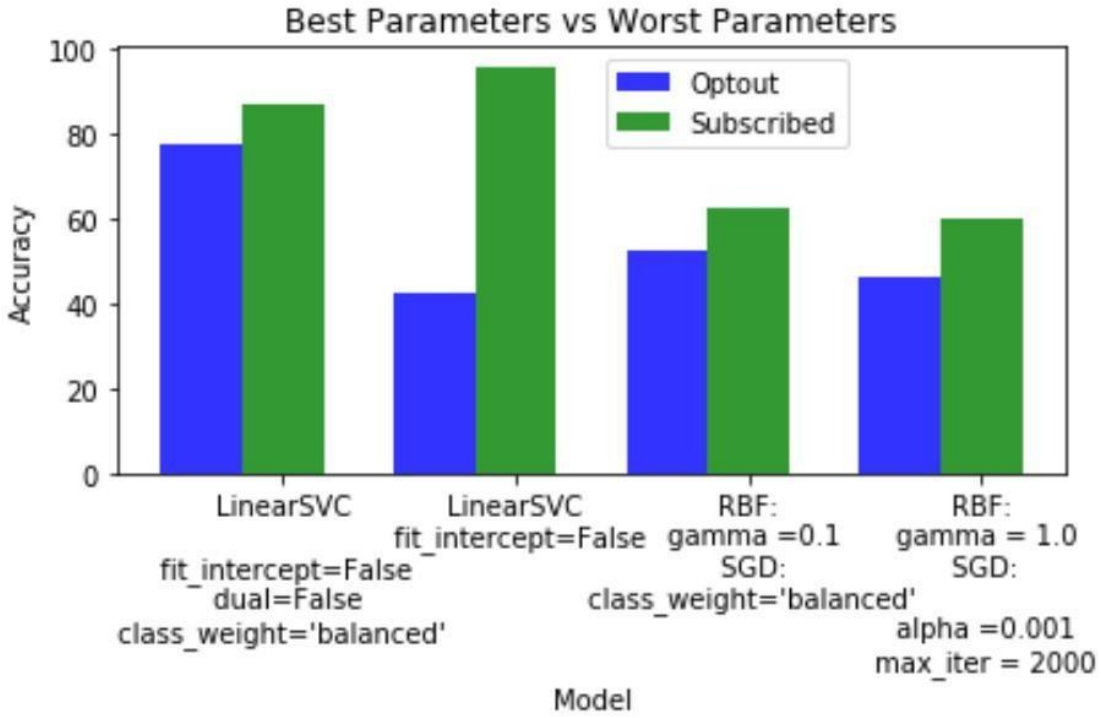


Solution

- Dropped most of the above models; kept only 3 which seemed to show slightly better results more consistently
- The format of the data, it’s imbalanced examples and the features used were the problem
- Applied One-Hot-Encoding and changed other features of the dataset to suit the selected models
- Dropped a few features, included some which were not used earlier
- Tuned the parameters and narrowed down the useful models to 2 with the below parameters:
    - LinearSVC(fit_intercept = False,dual = False, class_weight = 'balanced')
    - RBFSampler(gamma= 0.1, random_state=1); SGDClassifier(max_iter=1000, class_weight = 'balanced')
- LinearSVC provided the highest accuracy, RBFSampler with SGDClassifier was good enough to be included as well

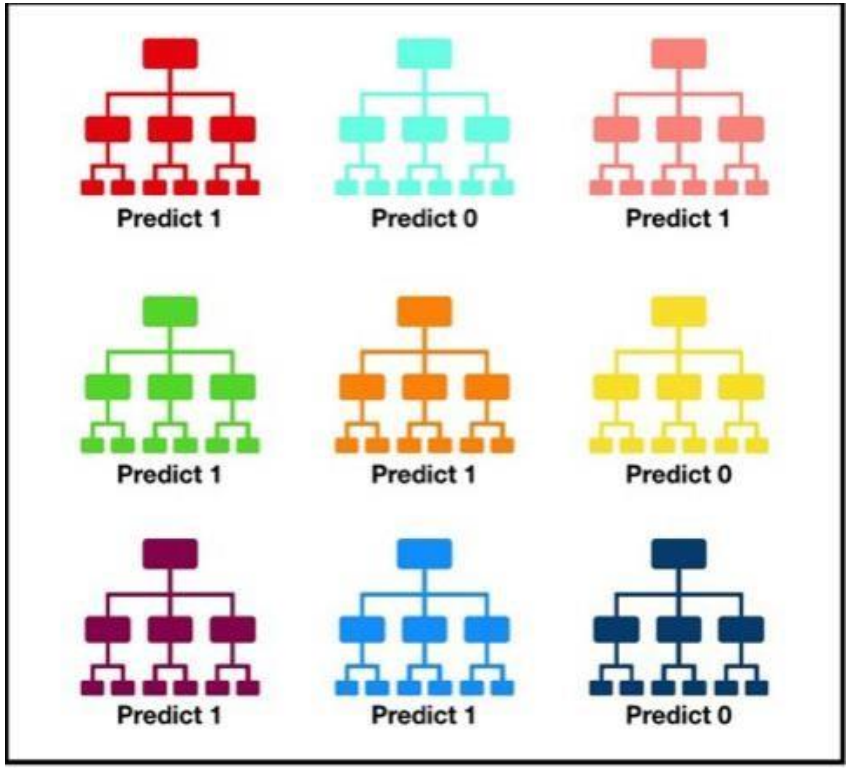
SVM-Final Results

- LinearSVC produced a good accuracy of 77.3% for Optout and 85.1% for Subscribed with the best parameters
- RBF+SGD produced a mediocre accuracy of 53% for Optout and 62% for Subscribed with the best parameters



Random Forest

- Random Forest consists of a large number of individual decision trees that operate as an ensemble
- Each tree gives us a class prediction and the class with the most votes becomes our prediction
- Random Forest uses bagging and random features when building the individual trees to create a forest of uncorrelated trees



Tally: Six 1s and Three 0s

Feature Extraction

- Recursive Feature Extraction (RFE):
  - Retrieving the top 3 features using the logistic regression algorithm

- The features taken into account are:
  - Profile.Id,Signup,Last.Open,Last.Click,Opt out.Time,Opens,Clicks,Lifetime.Message,r eferral_source,Top.Device, Geolocation.City,Domain
- The target variable is the ‘Engagement’
- Retrieving the 3 most favorable features with the following ranks:

```
In [16]: model = LogisticRegression(solver='lbfgs')
         rfe = RFE(model, 3)
         fit = rfe.fit(X, Y)
         print("Num Features: %d" % fit.n_features_)
         print("Selected Features: %s" % fit.support_)
         print("Feature Ranking: %s" % fit.ranking_)
```

```
Num Features: 3
Selected Features: [False  True  True False  True False False False False False False False]
Feature Ranking: [10  1  1  2  1  5  6  7  8  9  4  3]
```

- Random Forest Algorithm produced an accuracy of 96.5% for subscribed and 80% for optout, which is the highest of all 3 types of models.

Conclusion

Decision Tree

- Opt-out Accuracy: 60.8%
- Subscribed Accuracy: 67.6%

SVM

- Opt-out Accuracy: 77.3%
- Subscribed Accuracy: 85.1%

Random Forest

- Opt-out Accuracy: 96.5%
- Subscribed Accuracy: 80%

References

1. https://towardsdatascience.com/optimizing-hyperparameters-in-randomforest-classification-ec7741f9d3f6
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4. http://chrisstrelioff.ws/sandbox/2015/06/08/decision_trees_in_python_with_scikit_learn_and_pandas.html
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