Assigning Grades to Sales Leads with Classification

by Michael Weber

You can follow the code and all other additional resources at:

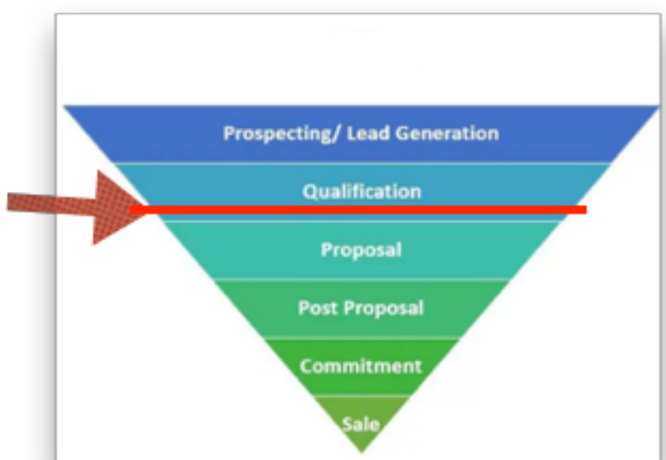
```
https://github.com/MichaelWeber2050/Project_3
```

Motivation

I wanted to use ML to tackle a real world problem and build something using a supervised learning classification model that could be an asset to the current business climate.

Nearly every business relies heavily on sales for revenue and market share and I saw an opportunity in the sales funnel to optimize the handling of qualified sales leads through grading and prioritization. Many companies use ML modeling for forecasting and budgeting at a high level but I wanted to create something for the salesperson to use in their day to day work life to improve overall sales performance company-wide.

The Sales Funnel



I thought that by giving grades to the qualified leads before they are handed off to the sales person (red line and arrow) I can increase efficiency of each sales person **saving time, increasing exposure to "winnable leads", and giving the company more chances at higher sales revenue numbers.**

Data

I used sales data with **Win and Loss binary target results from IBM Watson Analytics Blog** [https://www.ibm.com/communities/analytics/watson-analytics-blog/sales-win-loss-sample-dataset/ (https://www.ibm.com/communities/analytics/watson-analytics-blog/sales-win-loss-sample-dataset/)](https://www.ibm.com/communities/analytics/watson-analytics-blog/sales-win-loss-sample-dataset/)

The **original data had 78k observations and 19 features including the target variable "Opportunity Result"**

Other features included Business Sector in the form of groups and subgroups, Region or location 6 categories in the USA, the client company size by employee count, revenue and if they had purchased in the past and then 7 columns with data about the amount of time an opportunity took to either become a sale Won or Loss.

Data Cleaning and EDA

I found there were **some missing values** and also **some zeros** for the some of the quantitative feature values so I **removed those from the dataset.**

EDA poking around found and filtering by my target variable showed some of the results below:

	Mean			
Feature	**Won**	**Loss**	**Diff**	**% Diff**
Revenue From Client Past Two Years	0.78	0.24	0.54	69%
Opportunity Amount USD	97087	72962	24125.00	25%
Total Days Identified Through Closing	8.59	19.10	-10.52	-122%
Total Days Identified Through Qualified	7.69	18.83	-11.14	-145%
Reseller	0.54	0.42	0.13	23%
Ratio Days Identified To Total Days	0.07	0.24	-0.18	-262%

Minimum Viable Product is K Nearest Neighbors

After initial cleaning I used **one hot encoding** to modify my **categorical features** and with train test split used a **Logistic Regression Model & K Nearest Neighbors** on plain train data to get a baseline and to determine next steps.

LR scored faily well 77% accuracy But KNN scored surprisingly well at 90%

I actually also used a Linear Regression model and converted my target variable to binary 0 for Loss and 1 for Win and ran that model to check coefficients of my features and found similar to above the features with days to close were the most predictive. But I realized these are considered leaky data features because at the time a sales person receives a lead they cannot know how long this lead will take to close so I decided to remove those 7 features.

More Models

I tested many models and found many were similar scoring but Support Vector, Random Forest, ADA Boost seemed to perform best and Support Vector and Random Forest take forever to run so I chose the ADA Boost.

XGBoost Classifier is chosen

But after reading up more I found X Gradient Boost Classifier to be more suited to my needs of robust prediction power with speed for binary classification. XGBoost also helps to reduce overfitting and run a lot of the tuning through Cross Validation under the hood.

Dealing with Class Imbalance

I tried 3 techniques to balance my classes with Oversampling: **Random Oversampling, SMOTE, ADASYN**

I had 77% Loss 23% Won class imbalance so accuracy wasn't proving a good metric and I wanted to give my model more observations of the minority class to train on.

ADASYN seemed to give me the best results of increased F1 score I think because it uses density distribution to determine the synthetic minority points and I read it also adaptively changes the weights of the different minority samples to compensate for the skewed distributions.

Tuning XGBoost Classifier

After training on the synthetic balanced data set I also began to tune the various hyper parameters within the XGBoost Model. max_depth learning_rate n_estimators gamma min_child_weight subsample and objective.

Tuning these slowly but surely with trial and error and GridSearch gave me a small but sufficient increase in F1 scores and AUC.

Cross Validation

Before the test set, I chose 10 fold Cross Validation and split my data to train, val, test for a nice final variance mitigation.

FINAL RESULTS

F1 Score 81 AUC Score 83

CONCLUSION

The model is not super predictive but I think it does well enough to provide some definite value and can handle a grading system as it is now. A company deploying this model to grade their qualified sales leads as they are handed off to the sales person will most certainly see a boost in performance.

Future Work

I would like to bring in more data because this set was rather narrow in scope(mostly just automotive industry and IBM)

I began a **Flask Web App** but it still needs a lot of work.

I'd also like to build this direct into a company's sales process for automated distribution of graded sales leads for best implementation.