Project Report

A Business Case-study: Using Data to Bring Customers Home

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I. Introduction

The game of online retail and e-commerce has changed a lot over the past few years. Offline purchase and local stores have been replaced by hosting online stores. This paper explores a business case-study of one such e-commerce company: Wayfair. Wayfair is an e-commerce retailer that sells furniture and other home goods. While they sell to individual consumers, they also have a large B2B (Business-to-Business) division that sells to business customers such as interior design firms, contractors, hotels and universities.

As a data-driven company, they ensure that their B2B customers receive best-in-class service by leveraging data science models to predict customer needs and purchasing patterns. They primarily aim to reinvent the way the world shops for home and utilizes machine -learning models heavily in many of their departments including marketing, sales, and operations teams to guide business decisions. Often times, business vendors bring in most profits and it becomes really important for a company to personalize efforts for them and retain them and take appropriate measures if they are not retained.

Keeping this in mind, Wayfair hosted a challenge this year for which they released their B2B customer interaction dataset that will be used here. The goal of the challenge was to build a model to predict customer behavior for Wayfair. The goal of our project is to gain insights from the business customer data like customer information,sales call records, purchase history etc. and build predictive models to work on the following problems:

1. B2B customer conversion (classification): Whether a B2B customer will purchase or not in the next 30 days
2. B2B customer expected revenue (regression): How much a B2B customer will spend in the next 30 days.

Our case-study focuses on certain research questions that help us reach towards our final goal for prediction of B2B customer conversion and the expected revenue. However, one of our main goals is to be able to focus on the interpretable and explorable approximations of Black Box machine learning frameworks. Oftentimes, we have high dimensional customer interaction datasets to work with and the goal ultimately shifts from *understanding the customer behaviour analytically to prediction problems that are mostly handled by the black-box algorithms.* Our work heavily explores multiple feature selection techniques and identification of different feature subsets. Important feature subsets can help in analytically understanding the customer behavior. Identification of actionable features associated with customer retention can mainly help businesses also turn the non-retaining customers into the retaining customers if we can identify the main features and use strategies around those features.

1) Can we use data adaptive machine learning algorithms to predict Whether a B2B customer will purchase or not in the next 30 days.

a. There are an overwhelming number of features in the dataset. What are the most important features that help in the prediction of the conversion.
b. What techniques can be useful in determining the right feature-set?
c. Determine the optimal number of features in predicting whether a customer will purchase or not
d. Infer different feature sets to see if there is a logical explanation and interpretation of why some features are important over others and see if we can personalize efforts on customers that don't convert.
e. What modelling strategies best help in predicting the score?

2) What are the most appropriate methods for tidying the dataset? How to handle missing data, categorical data?
   a. How do we make sure our results are not biased?
   b. Will missing data imputation improve our prediction or yield high-performing feature-sets?

   c. Does missing data have any effect on feature subset selection?

3) Data-set is highly unbalanced. What are the appropriate sampling techniques to deal with class imbalance since there's a huge amount of missing values too?
   a. Identify and implement appropriate resampling techniques to deal with class imbalance.

4) How to develop an intuition from the dataset given the high dimensionality of the problem ?

a. Are we able to produce interesting visuals demonstrating the relationship between the target variable and the associated features?
b. Perform exploratory Data Analysis

II. Dataset

No longer just a techie buzzword, big data is transforming the retail sector to improve customer experience and increase profits. Today we are seeing many retailers pivot from exploratory technology pilots and experiments to making permanent investments and changes to organizational structures and capabilities. As a company, Wayfair knows that data democracy is critical to success. As a data-driven company, they ensure that their B2B customers receive best-in-class service by leveraging data science models to predict customer needs and purchasing patterns. They released their B2B customer interaction data to solve two problems which are also our target variables for this project:

1. B2B customer conversion(boolean value): Whether a B2B customer will purchase or not in the next 30 days i.e. indicating **retention**
2. B2B customer expected revenue(numeric value): How much a B2B customer will spend in the next 30 days i.e. indicating revenue

The entire dataset is divided into two parts:

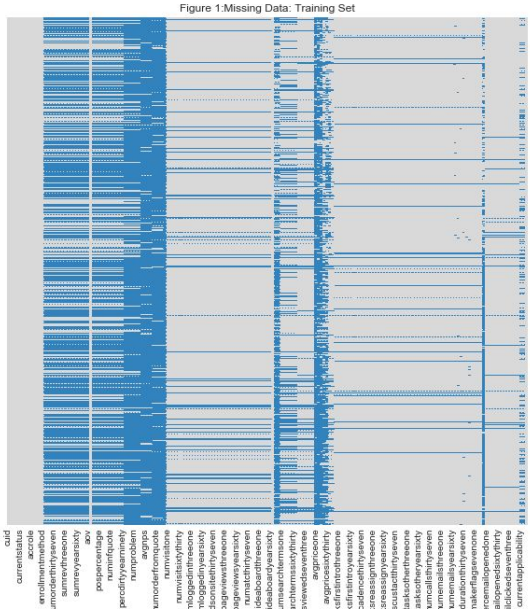
1. Training data: This data includes 181 features which can be divided into different classes depending on their functionalities. These are:
   a. Two outcome variables: This class contains the two outcome variables- convert_30 and revenue_30
   b. Customer: This class contains basic information about a customer like type, role, team, status, etc
   c. Enrollment questions: This class contains information like number of employees, number of purchases, total cost of purchases per year, etc
   d. Order: This class contains order information like number of orders, size, influence, etc over a time frame
   e. Satisfaction: This class contains customer satisfaction information over a period of time
   f. Visit: This class contains information like number of visits to the site or favorites list over a time frame
   g. Search
   h. SKU: This class stands for Stock Keeping Unit. It contains information like average price of a product viewed over a time frame, etc.
   i. Task: This class contains task information like introduction, cadence, reassignment and others over a time frame
   j. Call: This class contains call information over a time frame
   k. Email-BAM: This class contains information about emails exchanged between customer and sales representative
   l. Email-Wayfair: This class contains information about email subscriptions of Wayfair
2. Holdout data: This data includes all the features except the outcome variables for a different set of customers. We will use these features to predict the missing outcome variables.

III. Methodology

1. **Data Cleaning:** The dataset contains 10 categorical features and 170 numerical features. Our first method is to check for missing values to give us a better

understanding of how to work with real-world data. Often, data can have missing values due to a variety of reasons, for example, with survey data, some observations may not have been recorded. It is important for us to analyze our data, and get a sense of what the missing values are so we can decide how we want to handle missing values for our machine learning models. So, we then check for missing values in the training dataset.

Figure 1:Missing Data: Training Set

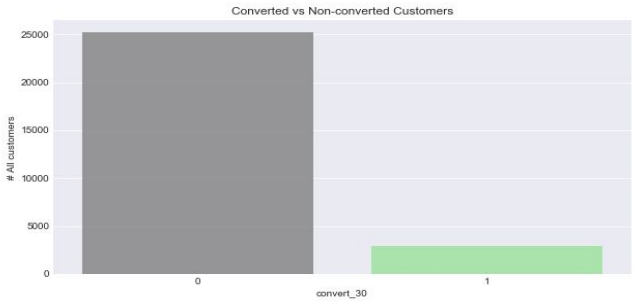


From the above Figure 1 we can observe that there seems to be a lot of missing values in numerical features. While if not all, some of them might be useful in modeling. One way to handle these missing values is to simply remove all the features that contain a lot of missing values because it might be cheaper for us to spend time avoiding missing data than estimating the right values for them and it also reduces the uncertainty of data. Second way to handle the data might be to define a strategy and impute these missing values based on the strategy. One of the most common strategies is to replace the missing values with a 0 value or using a median value.

We use the strategy where for customers who did not convert into buying products from Wayfair, we replace the missing data for these customers with a 0 value. For customers who did convert in other words bought products from Wayfair, we replace their missing value for a particular feature with a median value of that feature. We do this to reduce the bias introduced in our models as some of our features have over 60 per cent missing values and the number of conversions for customers is also low.

2. **Handling Categorical Data:** Categorical data are variables that contain label values rather than numeric values. The number of possible values is often limited to a fixed set. Many machine learning algorithms cannot operate on label data directly. They require all input variables and output variables to be numeric. In general, this is mostly a constraint of the efficient implementation of machine learning algorithms rather than hard limitations lon the algorithms themselves. This means that categorical data must be converted to a numerical form. This involves two steps: Integer Encoding and One-hot Encoding. As a first step each unique category value is assigned an integer value. This is called label encoding or integer encoding and is easily reversible. For categorical variables where no such ordinal relationship exists, the integer encoding is not enough. In fact, using this encoding and allowing the model to assume a natural ordering between categories may result in poor performance or unexpected results. In this case, one-hot encoding can be applied to the integer representation. This is where the integer encoded variable is removed and a new binary variable is added for each unique integer value. We use one-hot encoding for all our categorical variables.
3. **Normalizing and Standardizing Data:** Normalization often also simply called Min-Max scaling basically shrinks the range of the data such that the range is fixed between 0 and 1(or -1 if there are negative values). It makes training less sensitive to the scale of features, so we can better solve for coefficients. The use of a normalization method will improve analysis from multiple models. It also ensures that a convergence problem does not have a massive variance, making optimization feasible. It works better for cases where the distribution is not Gaussian or the standard deviation is very small. Standardization or Z-score normalization is the process of rescaling the features so that they'll have the properties of Gaussian distribution. It also helps to compare features that have different units or scales. Standardization and Normalization are created to achieve a similar target, which is to build features that have similar ranges to each other. We have applied the scaling and normalization on the entire dataset.
4. **Handling Class Imbalance:** Almost 89 per cent of customers do not convert to new purchases in 30 days. Imbalanced classes are a common problem in machine learning classification where there are a disproportionate ratio of observations in each class. Most machine learning algorithms work best when

the number of samples in each class are about equal. This is because most algorithms are designed to maximize accuracy and reduce error. There are several techniques we've explored in the case-study that can be used in dealing with class imbalance. The first method is over sampling the minority class. In this method we add more copies of the minority class. This can be a good choice when you don't have a ton of data to work with. The next method we experimented with was undersampling. Undersampling can be defined as removing some observations of the majority class. But the drawback is that we are removing information that may be valuable. This could lead to underfitting and poor generalization to the test set. The last technique is to generate synthetic samples. This is a technique similar to upsampling to create synthetic samples. We have used imblearn's SMOTE or SYnthetic Minority Oversampling technique. SMOTE uses a nearest neighbors algorithm to generate new and synthetic data we can use for training our model. The Figure 2 below shows the class imbalance against converted and non-converted customers over a histogram.



5. **Feature-Selection Techniques:** This case study requires a lot of exploration with different feature selection techniques to extract the best performing feature subset. There are also an overwhelming number of features and there is a need to make the model simpler for the interpretability purposes, to reason out and tackle the business problem in such a way that there is an explanation and logical reasoning behind the important features.

1. Filter Method: In this method, we basically use Pearson's Correlation Coefficient to remove the uncorrelated features. The filtering here is done using correlation matrix and it is done using Pearson correlation. All the relevant features whose correlation with the target (more than 0.2) were extracted. Correlation between the features was checked and the highly correlated features were dropped to remove redundancy. This method outputs feature sets containing: 1) Days since last order 2) Number of online visits in the past 1 day 3) Number of online visits in the past 1-3 days 4) Number of online visits in the past 30-7 days 5) Number of online visits in the past 60-30 days 5) Number of ATCs (Add To Cart) in the past 7-3 days 6) Number of visits in the past year 7) Number of seconds on site in the past 7-3 days 8) Number of ATCc in the past 30-7 days 9) Days since last visit 10) Number of search terms in the past 30-7 days 11) rollup - unmanaged

2. Wrapper Method: The Recursive Feature Elimination (RFE) method works by recursively removing attributes and building a model on those attributes that remain. It uses accuracy metric to rank the feature according to their importance. The RFE method takes the model to be used and the number of required features as input. It then gives the ranking of all the variables, 1 being the most important. It also gives its support, True being relevant feature and False being irrelevant feature. This technique outputs 'percdirtythirty','quoteconrate','numvisitone','numvisitthreeone', 'numvisitseventhree','numvisitthirtyseven', 'numvisitsixtythirty','numvisityearsixty', 'numatcone', 'numatcthreeone','numideaboardone','numideaboardseventhree','numtasksfirstintrosixtythirty','numemailsone','percemailopenedone','percemailopenedseventhree', 'percemailopenedyearsixty', 'roll_up_Unmanaged', 'currentstatus_Enrolled','customersource_Internal Customer Scrape', 'customersource_Social - Paid' all of which are further discussed in the future section. Although there was some degree of similarity between the feature sets computed by the 2 techniques, we did discover some important feature sets from this method.

We fit a logistic regression model over the selected feature sets. The idea is to compare the models with a variety of different feature subsets. Notice here that we are not yet diving into the modeling part or using logistic regression for the purpose of prediction. We then see that the accuracy of the model when using all features in the dataset is 77% and when using 12 selected features is 75%. This does not tell us a lot about the subset. Although, it does not help in boosting the baseline performance, it is intuitive that most of the features in our dataset are not relevant. To further boost the performance, we explore different feature selection techniques.

3. Third method was based on computing chi-squared stats between each non-negative feature and class. This score can be used to select the n_features features with the highest values for the test chi-squared statistic from X. Dataset contained a lot of negative values and hence it was already processed to create a normalized dataset to perform Chi-square tests. This particular method yielded the

best performing set which was eventually revealed when different modelling techniques were applied. More so, later on it became a little intuitive to understand why this set performs better than the rest. It basically outputs 30 variables after which it starts to underperform. It combines all of the features from the previous 2 methods and as the number of features is more than the previous 2 methods - it turns out slightly better than the rest.

4. Embedded Method: Lasso Regularization

Lasso penalizes all of the features if it is not relevant. it penalized the coefficient and makes it 0. Hence the features with coefficient = 0 are removed and the rest are taken.

6. **Modeling Strategies:** For the modeling strategies each of the five models were fit with all the features and then the feature-subsets extracted via techniques described above. The models we used are Logistic Regression, Decision Trees, Random Forests and Gradient Boosting.

IV. INTERPRETABILITY OF FEATURE SUBSET SELECTION

Various feature selection techniques as described in the previous section were employed for identifying actionable features to predict and ideally boost conversion. While there is a lot of overlap in the relevant feature subsets, this section essentially discusses all of the relevant features from all of the methods and how they can be inferred in the business context to boost conversion.

First technique used was the ***filter method*** based on using Pearson's correlation coefficient. As the name suggests, we filter out the irrelevant features, select the relevant ones and then build the model. This model outputs many features around 'Number of Visits' like **Number of online visits in the past 1 day** , **Number of online visits in the past 1-3 days** , **Number of online visits in the past 30-7 days** ,**Number of online visits in the past 60-30 days.** While the Number of online visits metric does look a little repetitive, it does bring in different perspectives: It brings in the powerful idea of user segmentation - New users v/s Old users. This particular metric can be useful in determining and designing new strategies around new and old users. New visitors interact much differently than returning visitors. In most cases the new visitors try to get familiar with the brand, and figure out if the company is a credible or appropriate fit for their needs. In the context of Wayfair, this metric can definitely prove a lot more useful. When there is a large number of new visitors, one of the possible strategies could be to add them to their marketing list, send them promotional emails or give them a generous discount on their first purchase. In case of a large number of old visitors. When there are a large number of return visitors, it might be a good idea to tailor a personalized experience for them which is more consistent with their needs. Personalizing efforts to remind them of their previous purchases, product views, or interactions in general can help in boosting sales. Thus, this metric definitely does help in predicting purchase and if used wisely can help in channelizing efforts to convert the non-buying ones into the buying ones. The concept of a returning customer being easier to convert than a new customer can be validated by this set of relevant features as given out by the filter method.

Other important feature spit out by the model is: **Number of search terms in the past 30-7 days**. This again could logically be very important metric since it could essentially lay emphasis on site search: what the customers typically want and what pages aren't meeting their needs. If the number of search terms are low for a number of different products~ it probably means that search terms could be more specific and most likely coming from existing or returning customers who came back, knowing what they want. If the number of search terms are general and appear larger in number, then it may mean customers can't find what they are looking for. Another important perspective from this metric could be to test the Search Results Page. Are the customers able to find their items of interest on Page 1? It becomes very important to show the most relevant results *first.* Showing related products or recommended products to the returning customers can definitely pass the personalization test.For eg. showing Top picks. This is a very simple personalization tactic and can boost conversions. Furthermore, features like **Days since last order** and **Days since last visit.** These metrics could specifically be important in the context when return customers Customers visit the website, come back more times, depending on the price point and also on why the brand exists, and then maybe close the deal. These metrics also enhance the understanding of "how long" it takes for customers to buy from the website and is that behavior different across different segments of the website customers. If exploited the information wisely, it can definitely help optimize marketing campaigns, promotions, other efforts to boost conversion. Next, filter method places importance on **Number of Add To Carts in the past 30-7 Days -** While it is an intuitive one, there are many factors around this feature that can lead upto the actual conversion - Is there a guest check out option to enable faster processing (even if it's a bulk order)? Is there any shipping estimate provided when the product is added to the cart? Now that the customer has already made up his mind but is only a few clicks away - Are there any personalized efforts involved in reminding him to complete the purchase? Lastly, **Number of Seconds** on the website inarguably is another very important metric - How long is the website able to interest the user? Is the website search efficient in producing relevant results quickly? Again, is there any personalization to keep the user engaged? How is the product recommendation working. If the number is really low - we can definitely predict a higher bounce rate - The bounce rate is the rate at which new visitors visit the site and immediately click away without doing anything. Common problems may include

poor website design, low usability, or higher load times that could potentially affect the conversion rates.

Second Feature selection technique was Recursive Feature Elimination and we get a number of features around various domains. While just like filter method, RFE Outputs **Number of ATCs** and **Number of visits** as important feature groups, it also places importance on customer satisfaction features like "**Percentage of orders in the past 30 days that were a 'dirty' (problematic) order**". E-satisfaction is definitely an important factor and lesser the number of problematic order, the greater the satisfaction. While this metric can be a direct metric by itself, there are a range of factors around this metric which can still help if the percentage of dirty orders is high. Customer obsession can be of the greatest value - How is the company tackling dirty order issues? how efficient and fast is the dirty-order and re-order processing? How does the company make sure it is not losing on its valuable customers?
Is there any financial or product based incentive, especially because the case study concerns B2B customers and the orders associated with such customers are the bulk orders.
Next important feature is the "**Number of items in the favorite List**" since it can potentially lead to "**Number of items in the cart**".
More so, another feature group identified via this method is "**Percentage of Emails Opened from Wayfair**" and "**Number of Emails between Customer and Sales Representative**". Email marketing is one of the most common forms of product marketing - often times A top priority for email marketing is to increase the subscriber engagement, which in turn has the power to increase sales, average revenue per customer and .
in general keep the customers informed about the new launches, on-going promotions and recommendations around their past purchases and in some way anticipate their future needs.

Chi-Squared test computes a set of features, most of which are a combination of features selected by the first 2 methods. This feature set performs better than the rest since it captures all of the important features from different feature subsets like "**Days since Last order**", "**Percentage of Dirty orders**", **Number of visits in the last few days**, "**Number of seconds on the site**", "**Number of Logged in sessions**",
"**Number of ATCs**", "**Days since Last Visit**", "**Number of search Terms**" and "**Percentage of Emails opened**".

V. Results and Evaluation

The results that we obtained by modeling the different feature sets is given below. Inference from different feature sets has been discussed in the previous section. For Logistic Regression we get:

Feature set obtained from	Accuracy	Recall
All 181 features	77	0.28
Filter method	75	0.27
Wrapper method	75	0.30
Chi-square tests	78	0.30
Embedded method	73	0.29

For Decision trees we get:

Feature set obtained from	Accuracy	Recall
All 181 features	64.20	0.33
Filter method	66.26	0.33
Wrapper method	63.18	0.31
Chi-square tests	76.53	0.46
Embedded method	65.49	0.33

For Random Forests we get:

Feature set obtained from	Accuracy	Recall
All 181 features	0.89	0.66
Filter method	0.88	0.65
Wrapper method	0.87	0.67
Chi-square tests	0.89	0.67
Embedded method	0.88	0.64

VI. Statement of Contributions

The project is a work of joint efforts by both of the partners. While we divided the implementation part, all of the portions were jointly discussed,evaluated and inferred by both

the team members. We collaborated online for code reviews, presentations and reports.

- Devanshi Gariba- Class Imbalance, Feature Selection, Modelling
- Alefiya Naseem- Data Cleaning, Wrangling, Class Imbalance, Modelling

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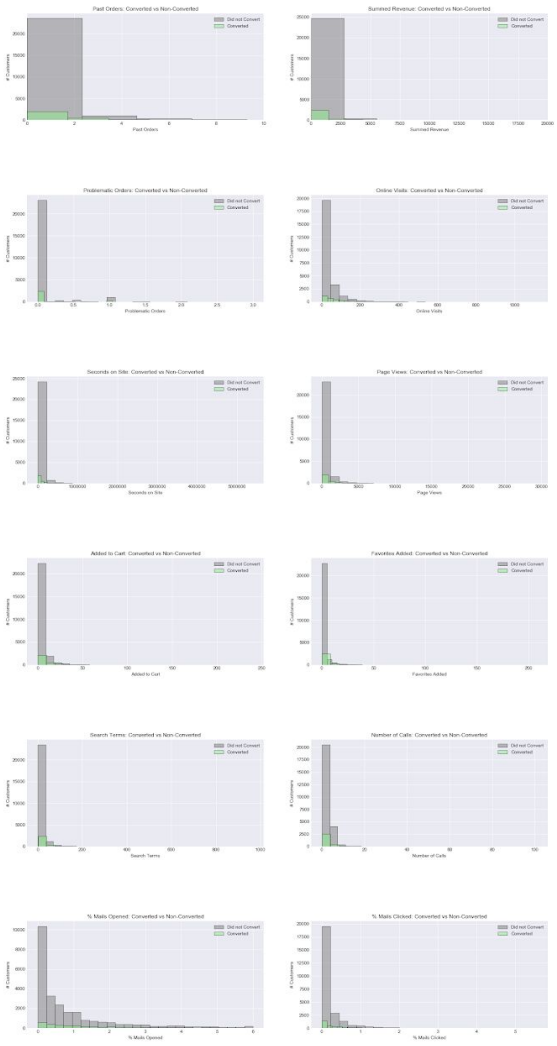
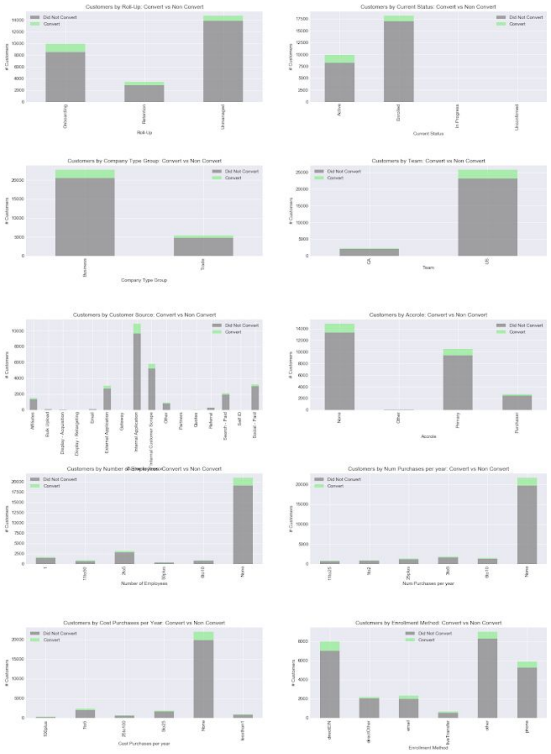
Appendix

Link to Github code:
https://github.com/alefiya-naseem/CustomerRetention-Revenue

The figure below shows the distribution of numeric features of converted and non-converted cutomers.





The Figure above shows the distribution of categorical features of converted and non-converted customers.