Uptake Data Science Case Study

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Introduction:

I followed standard data analytics practices & breaked down the case study in 5 parts.

Data Treatment(Missing Value and outlier fixing)
Descriptive/Exploratory Analysis of the Data
Data Modeling
Estimation of performance
Final conclusion

The Data understanding part became very clear after going through each column in the data description provided.

Type	Name	Description
Input Variables	custAge	The age of the customer (in years)
Input Variables	profession	Type of job
Input Variables	marital	Marital status
Input Variables	schooling	Education level
Input Variables	default	Has a previous defaulted account?
Input Variables	housing	Has a housing loan?
Input Variables	loan	Has a personal loan?
Input Variables	contact	Preferred contact type
Input Variables	month	Last contact month
Input Variables	day_of_weel	Last contact day of the week
Input Variables	campaign	Number of times the customer was contacted
Input Variables	pdays	Number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
Input Variables	previous	Number of contacts performed before this campaign and for this client
Input Variables	poutcome	Outcome of the previous marketing campaign
Input Variables	emp.var.rate	Employment variation rate - quarterly indicator
Input Variables	cons.price.id	Consumer price index - monthly indicator
Input Variables	cons.conf.idx	Consumer confidence index - monthly indicator
Input Variables	euribor3m	Euribor 3 month rate - daily indicator
Input Variables	nr.employed	Number of employees - quarterly indicator
Input Variables	pmonths	Number of months that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
Input Variables	pastEmail	Number of previous emails sent to this client
Target Variables	responded	Did the customer respond to the marketing campaign and purchase a policy?
Target Variables	profit	If the customer purchased a policy, how much profit (before marketing costs) did the company make on the policy?

Objective of the case study
Objective is to determine which set of customers the marketing firm should contact to maximize profit. The cost of marketing to a particular customer is $30. This cost is paid regardless of whether the customer

responds to our marketing or not. Only if a customer responds to our marketing, company earn a profit. Profit does NOT include the marketing cost.

Total Profit = Average profit per responding Customer * Number of customers responding - Number of customers to whom you marketed * $30

Data Treatment

Looking at the file training.csv ,i could figure out there were substantial NA values in many columns as follows

	custAge	profession	marital	schooling	default	housing	loan	day_of_week	profit
Total Missing	2014	71	10	2666	1618	184	184	787	7310
Percentage missing	24.45	0.86	0.12	32.36	19.64	2.23	2.23	9.55	88.74

As can be seen in the above table, in the train DataSet only 88% of the Profit value's are NA which effectively means only 12% of the campaign positively responded
For the profit column whoever not responsed i replaced thier profit as -$30 as per the guidelines
From this approach we can aggregate the total Profits as follows

Response	Profit
Yes	159720
No	-219300

Clearly the insurance company suffered loss overall(-59580) mainly because of targeting lot of customers.Thus there's dire need to optimize & customize which customers to target.

For the rest columns with NA values i imputed this missing values using MissForest package in R which is a popular implementation of random forest algorithm.
The rest of the columns has proportionally very less NA values so the imputation 'll work fine

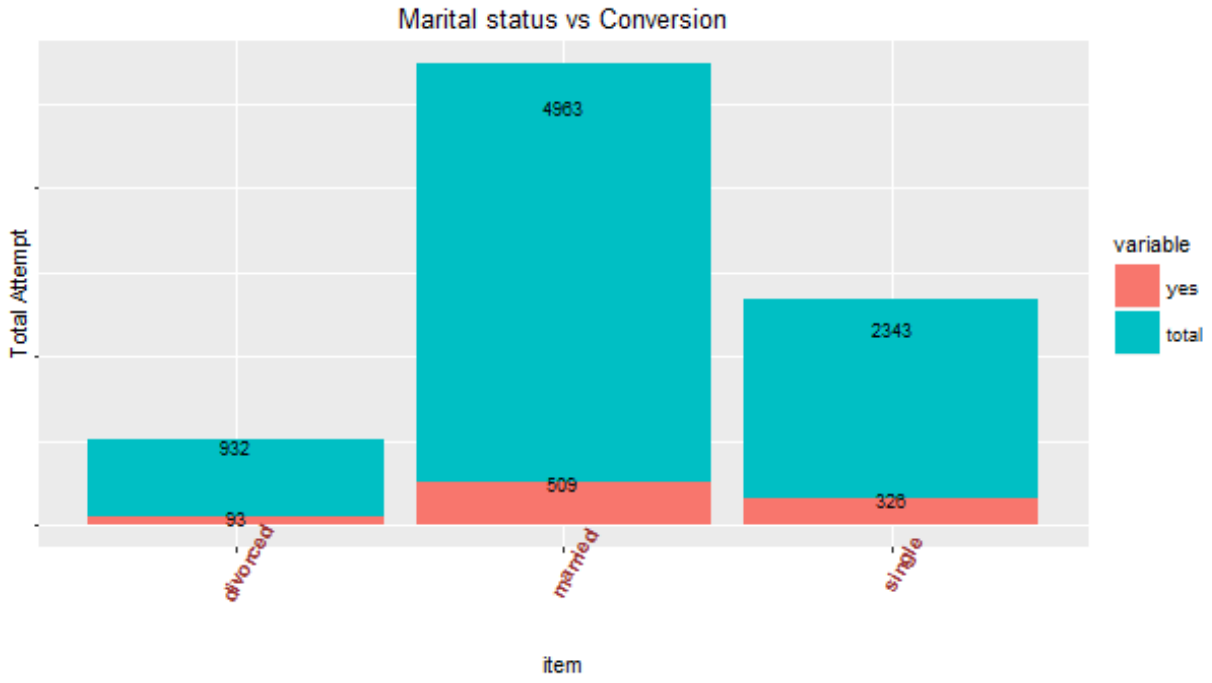
I used R to write code for imputation.

code:imputation code

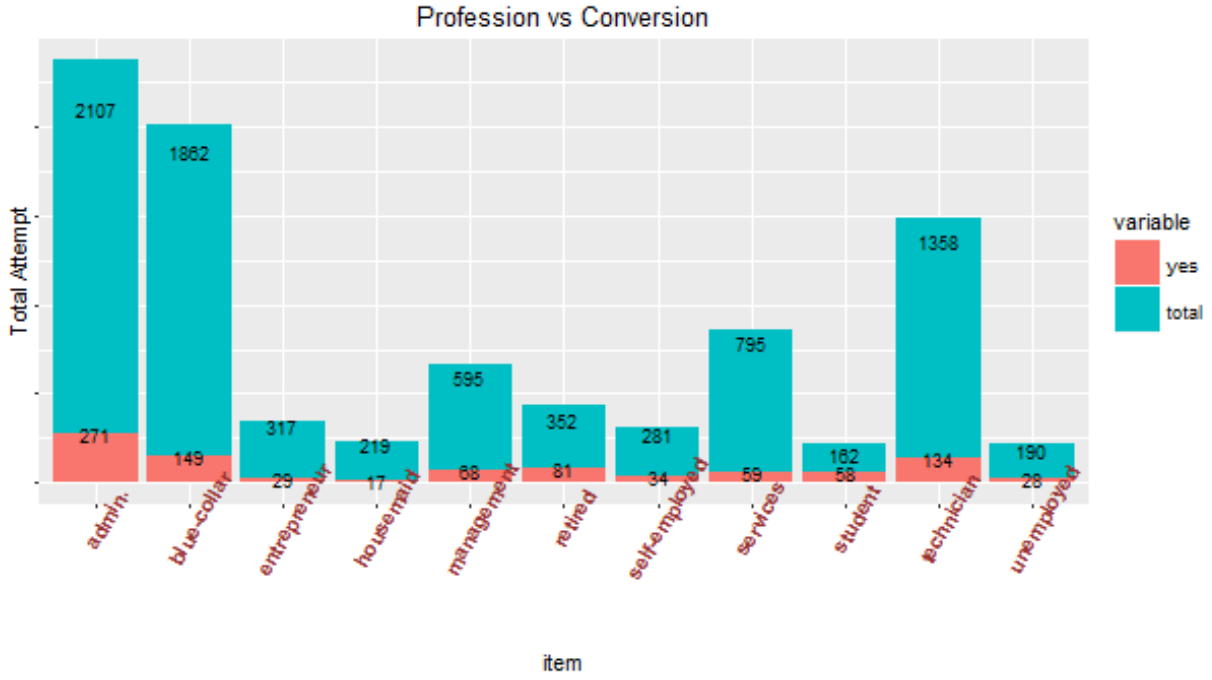
Exploratory Analysis

As a standard measure i performed univarate analysis of important categorical variables in the imputed data to try find their patterns with response variable.I felt stacked barplot could be the best visualization if the patterns are present.I got the following charts

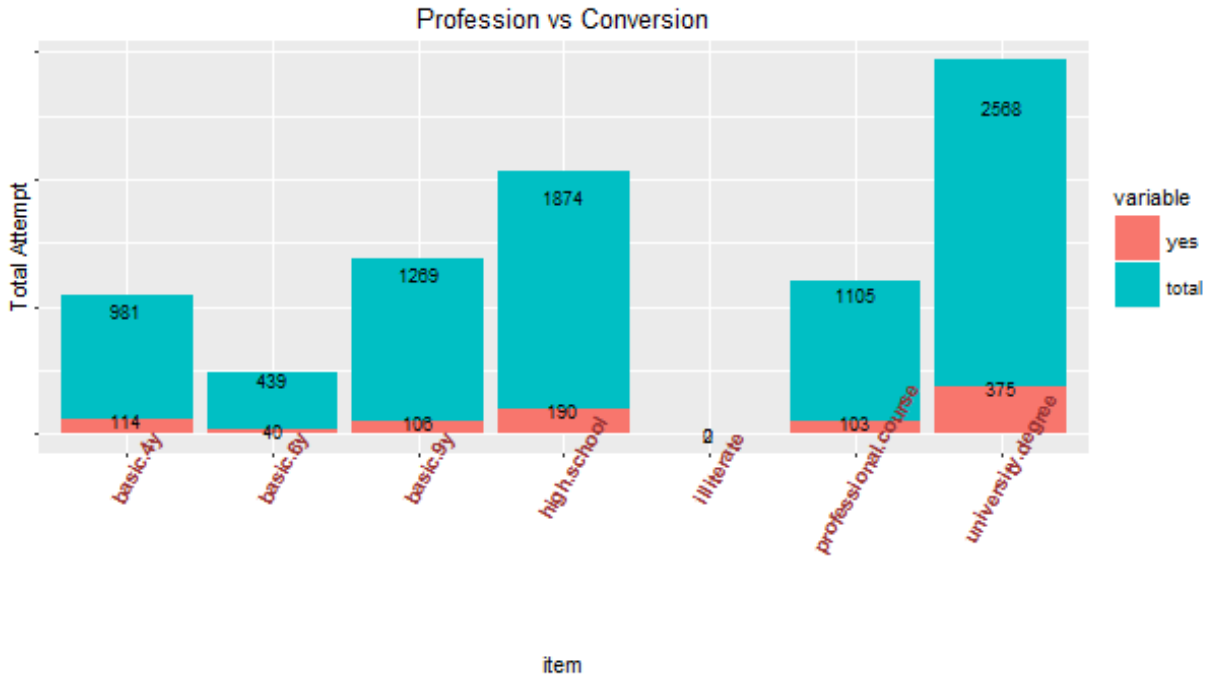
1). **Marital Status Vs response**



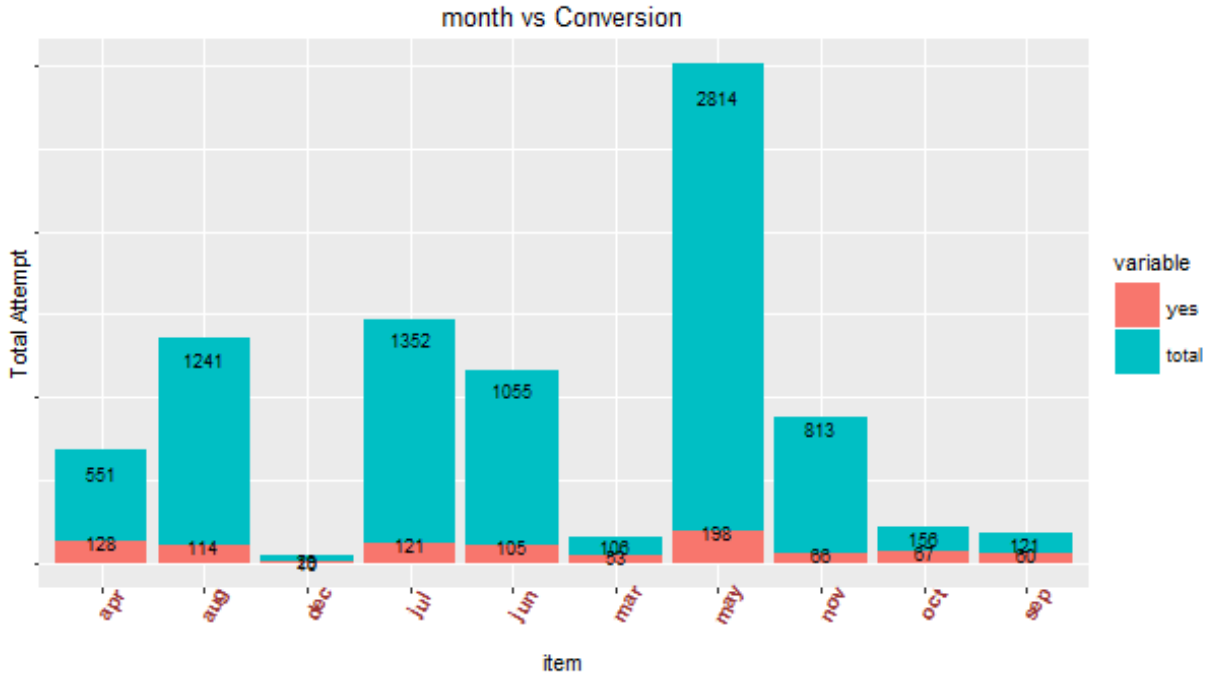
2). **Profession Vs response**



3). **Schooling Vs response**



4).**Month vs Resonse**



Looking at these charts, it is evident that none of the above categorical variable is independently influencing the campaign outcome extremely.

So it wont be a good strategy to run campaign based on just one category.It is quite possible that past campaign were loss making because of this trend.

I used R for all the Visualization
code:exploratory_analysis.rmd

Data Modeling

Thus, from the exploratory Analysis it is quite clear that we need to take into account all the 21 variables to predict the response outcome.

Please note: Because the no. of features were not that much & all the features, are more or less naturally independent (For ex age,month,contact) so i refrained from using PCA or any dimension reduction techniques

Because the predictor variables were both categorical & numerical.So i used following modeling techniques
1) Logistics Regression classifier
2) Random Forest Classifier
3) Support Vector Machine Classifier.

To test the the accuracy of each of these classifier, i checked it on validation set , K fold Validation sets as well Area under the curve(AUC) parameter.

Following are the results i got :

Technique	Validation Set	K Fold	AUC
Logistic	0.90	0.89	0.800
Random Forest	0.89	0.90	0808
SVM	0.901	0.90	0.782

So on an average all the classifiers performed equally well on validation set as well as for K folds.

Then,I tested each of this model on the file **testingCandidate.csv** to predict customer reponse. I got the following outcomes.

Technique	Yes	No
Logistic	906	31807
Random Forest	1720	31231
SVM	1285	31666

with 95% confidence interval.

Thus logistics Regression comes out as most conservative classifier whereas Random Forest is most optimistic.

To make the final prediction i took the majority voting on each three of the classifier decision i,e if 2 or more classifiers are predicting that the customers 'll respond then i'll run campaign for that customer. If 1 or less classifier is predicting that the customers 'll respond then i'll not run campaign for that customer.
The final results can be seen in the file **Final.csv**
I used Python scikit learn to implement each of the three classifier.

code: Modeling code

Conclusion.

The final aggregated results of combined classifiers was to target selected 1107 customers out of 33K customer base i,e 3%

so Projected Profit

1) Most optimistics when all 1107 customers 'll respond
   =Average profit per responding Customer*Number of customers responding - Number of customers to whom marketed* $30 = 171*1107* - *110*730=$156087

2) Least optimistics when only 50% 0f 1107 selected customer response (less plausible)
   =Average profit per responding Customer*Number of customers responding - Number of customers to whom marketed* $30 = 171*553* - *110*730=$61438.5

Thus,By Targeting above set of customers insurance company is very likely earn to significant profit even in the worst case scenario.I'll personally suggest insurance company to target around 5% of the total customers

Further Work.

1). The above Analysis is very trivial given the time constraint.
2). In future we can explore more of feature selection and sophisticated classifier's like neural networks to enhance our model.
3). Exploratory Analysis/Descriptve Analytics could be more extensive to find more correlation and independence relationships among the features
4). As per my experience i tried to implement Xtreme Gradient Boosting (XGB) for this problem for better accuracy on training data but somehow i couldn't implement it.

References

1) www.r-blogger.com
   2)www.kaggle.com
   3)www.analyticsvidhya.com

All the code & images can be found in code/image folder.

Skills Demonstrated

1) R { ggplot,data.frame,data.table}
2) Python {scikit learn,numpy,Pandas,Jupyter notebook}

3) Exploratory Data Analysis

4) Machine Learning

5) Business Understanding

I tried my best to show all the required & Preferred skills for the concerned Data Science Programmer internship position.