***Predicting the likelihood of E-Signing of loan based on financial habits***

Case Study: In the real world almost all the companies take data from some other sources and use those data to look into the financial history of the customers to determine whether they will be buying new stuff or not. Now take the case of a loan providing company it sets some criteria as screening terms and uses them to determine the chances of taking up a loan or not.

Also, those criteria work as leverage to find whether the person would be able to pay back the loan or not.

Objective: To develop a model to predict 'quality' applicants, in this case, study quality applicants are those who reach a minimum threshold part of the loan application process.

Business Challenge: In this case study we will take up the case of Fintech company, which is a loan providing company. Fintech has partnered with a P2P company which provides with real-time leads. The company tasks you with creating a model that predicts whether or not these leads will complete the electronic signature phase of the loan application (a.k.a. e\_signed). The company seeks to leverage this model to identify fewer quality applicants(e.g. those who are not responding to the onboarding process) and experiment with giving them different onboarding screens.

The reason for selecting the e\_signing process as the response variable is due to the structure of the loan application.

The official application begins with the lead visiting into the website after they opted to acquire it. Here, the applicant starts with the onboarding process to apply for a loan. The user begins to provide more financial information by going over every screen of the onboarding process. The first phase ends with the applicant providing his/her signature indicating all of the given information is correct.

Any of the following screens, in which the applicants are approved/denied and given the terms of the loan, is dependent on the company, not the applicant. Therefore the effectiveness of the onboarding is measured up to the moment the applicant stops having control of the application process.

Data: The data will include the financial history of the applicants which will be used to create risk scores that will be the basis of the culmination of our model. We will take into account the details provided by the p2p companies and then form the final algorithm that will be used to predict if the user is going to respond to our current onboarding process or not.

Deal with the codlings

Final conclusion:

Our model has given us an accuracy of 64%. With this, we have an algorithm that can help predict whether or ot a user will complete the E-signing step of the loan application. One way to leverage this model is to target those predicted to not reach the e-sign phase with customized onboarding. This means that when the lead arrives from the p2p, they may receive a different onboarding experience based on how likely they are to finish the general onboarding process. This can help the company minimize how many people drop off from the funnel. This funnel of screens is as effective as we, as a company, build it. Therefore, user drop-off in this funnel falls entirely on our sholders. So, with new onboarding screens built inteltionally to lead users to finalize the loans application, we can attempt to gt more than 40%of those predictd to not finish the process to complete the e-sign step. If we can do this, then we can drastically increase profit. Many lending companies provide hundreds of loan everyday, gaining money for each one. As a result, if we can increase the number of loan takers, we can increase the profits. All with a simple model!