Group members:

Scenario:

A credit card company is evaluating 4 bonus cashback strategies with the goal of generating more profits and attracting more new customers in the long run, and determining whether to hire an analyst to help them reduce the potential risk of approving a bad applicant.

Suppose this credit card company charges a 4% transaction fee to the merchant when its customers use the credit card. Currently, the credit card company offers its customers an unlimited 1% cashback on credit card spendings. The credit card company is considering offering some bonus cashback to its customers to stimulate the customers to allocate more of their monthly spendings into the credit card, as well as attracting new customers. The credit card company came up with four bonus cashback strategies, and its customers will earn 1% cashback on the first $1000 of the monthly spending on the credit card, and 1% plus bonus cashback after that. The bonus cashback can be any number between 1% and 2%. At the same time, the credit card company came up with a signup bonus for the new customers, which is a $50 statement credit after spending $200 in the month of signing up, and new customers can sign up using a referral link from a current customer, or sign up alone. If the new customers sign up by referral, both the referrer and the new customer would get $50 credits after the new customers reach $200 credit card spending in the first month of signing up; If the new customers apply alone, only the new customers will get $50 after reaching the spending requirement. The more bonus cashback that current customers get, the more likely they are going to send out referral links to their friends. However, there is a possibility that some new customers sign up just to get the signup bonus, which means the credit card company will obtain a loss if these 'bonus hunting' customers get approval. Therefore, the credit card company would like to consider hiring an analyst who has access to the new applicants' monthly spending on their other credit cards, and this analyst has a record of predicting the new 'spend around average' customers correctly at 80% of the time, and predicting new 'bonus hunting' customers correctly 90% of the time. The credit card company wants to know what is the maximum amount they can accept for using the service that this analyst provided.

Assumptions:

1. All customers paid in full at the end of the month (no interest rate)
2. No additional cost to the credit card company other than the cashback and bonus they offered to their customers
3. Assume all current customers are not bonus hunting
4. Assume we can observe the probability of being an economically good month and the probability of an economically bad month.

Note:

The main purpose of this project is to build on the mid-term project (team 17 for reference) and mainly focus on the credit card company's perspective on the new applicants, in terms of balancing the potential risks of approving a bad new applicant and potential gains of getting a great applicant. At the same time, this model will modify some assumptions and rules of the mid-term project to make the model closer to reality, and easier to use.

Another Note: Since the customers data are randomly generated, therefore the answers in the attached excel file may not match with this report, however, the approach is the same.

Solution Approach:

We generated 2000 customers' credit card spendings of the past two months randomly, and we were able to calculate the percentage changes of the monthly credit card spendings for each customer. Then, we categorized these percentage changes into 6 intervals, and counted the number of customers within each interval, and divided by the total number of customers to form a prior probability. Next, we obtained the average percentage change of monthly spending among the entire US credit card users from the Federal Reserve website, and categorized these data from the past 10 years into the same 6 intervals as before. By using similar calculations, we can obtain the probability of the monthly percentage change of the entire US credit card users, and we used these probabilities as the likelihoods of these intervals, and formed the following table:

Posterior Probability Distribution				
Number of customers	2000			
Change in Monthly Spending	**Prior Probability**	**Likelihood**	**Prior Probability * Likelihood**	**Posterior Probability**
<=0	0.4275	0.1203	0.0514	0.3267
0 - 0.05	0.1210	0.3609	0.0437	0.2774
0.05 - 0.10	0.1210	0.5038	0.0610	0.3872
0.10 - 0.15	0.0900	0.0150	0.0014	0.0086
0.15 - 0.2	0.0080	0.0000	0.0000	0.0000
> 0.2	0.1595	0.0000	0.0000	0.0000
		SUM	0.1574	

The Posterior probability gives us the probability that a customer’s change in monthly spending falls into these intervals, based on the customer's INDIVIDUAL spending behavior and overall TRENDS among the credit card users in the United States. The credit card company wants the bonus cashback rules to benefit the majority of its customers, so current customers are more likely to refer this credit card to their friends, and attracts more customers to apply for this card as a result. Therefore, we decided to design the bonus cashback based on the **POSTERIOR** probability, with the goal of covering the majority of the customers, and we categorized these Posterior probabilities into 4 intervals, and designed 4 cashback bonus rules, shown below:

CashBack Bonus Rules				
Posterior Probability Interval	**i_1**	**i_2**	**I_3**	**i_4**
0 - 0.1	0.0%	0.5%	1.0%	0.0%
0.1-0.3	1.0%	1.0%	1.5%	0.0%
0.3-0.4	1.5%	1.5%	2.0%	0.0%
>0.4	2.0%	2.0%	2.0%	0.0%

The following table is an example of applying the bonus cashback rules to corresponding Posterior Probability, for **demonstration only**(the filling colors are corresponding to the posterior probability intervals of the table above):

Change in Monthly Spending	***Posterior Probability***	***Bonus Cashback using i_1***	***i_2***	***i_3***	***i_4***
<=0	0.3345	1.50%	1.50%	2.00%	0.00%
0 - 0.05	0.2795	1.00%	1.00%	1.50%	0.00%
0.05 - 0.10	0.3769	1.50%	1.50%	2.00%	0.00%
0.10 - 0.15	0.0091	0.00%	0.50%	1.00%	0.00%
0.15 - 0.2	0.0000	0.00%	0.50%	1.00%	0.00%
> 0.2	0.0000	0.00%	0.50%	1.00%	0.00%

What is more, we assume all customers' monthly spending on the credit card depend on two factors: the state of the month, and the level of the bonus cashback they get, shown as follows (where X is the credit card spending of last month, and P is the probability of the economical good month):

State of the month	P = 0.9	1-P =0.1
Total Cashback (%)	**Good Month**	**Bad Month**
1<=i<=1.5	X	0.9X
1.5<i<=2	1.3X	1.1X
2<i<=3	1.9X	1.3X
Elsewhere	0	0

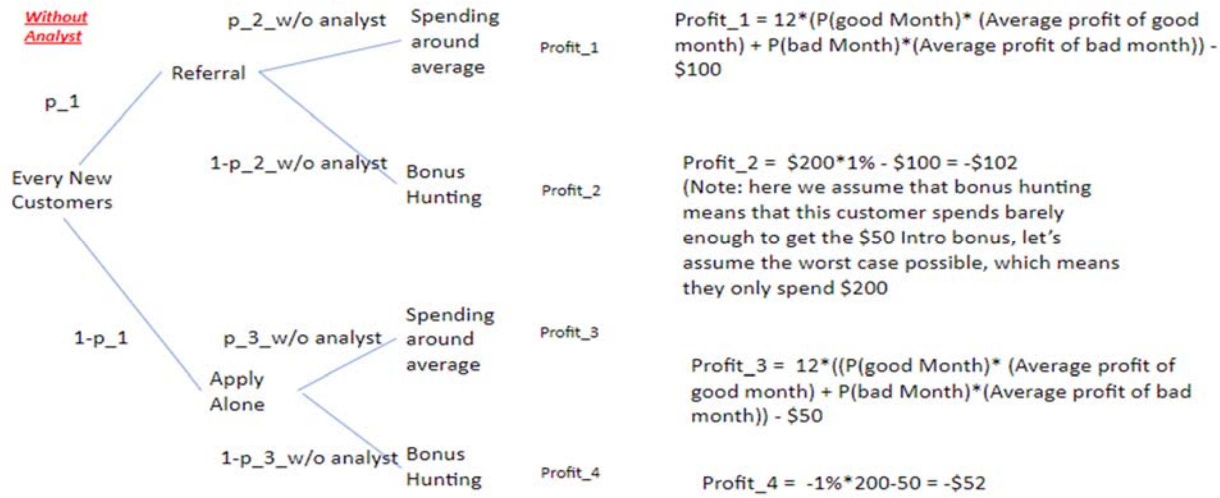
We can see that the higher the total cashback level a customer gets, the higher multiplier of spending will be. However, the multipliers are smaller in a bad month compared to a good month under the same total cashback level. As a result, profits can be calculated as follows:

Expected Profits Function (if monthly spending >1000)			
Cash Back %	**Good Month**	**Bad Month**	
1<=i<=1.5	(4%-1%)*X-(i-1)%*(X-1000)	(4%-1%)*0.9X-(i-1)%*(0.9X-1000)	
1.5<i<=2	(4%-1%)*1.3X-(i-1)%*(1.3X-1000)	(4%-1%)*1.1X-(i-1)%*(1.1X-1000)	
2<i<=3	(4%-i%)*1.9X-(i-1)%*(1.9X-1000)	(4%-1%)*1.3X-(i-1)%*(1.3X-1000)	
Elsewhere	0	0	
Expected Profits Function (if monthly spending <=1000)			
Cash Back %	**Good Month**	**Bad Month**	Note:
1<=i<=1.5	(4%-1%)*X	(4%-1%)*0.9X	i: Total Cashback
1.5<i<=2	(4%-1%)*1.3X	(4%-1%)*1.1X	
2<i<=3	(4%-i%)*1.9X	(4%-1%)*1.3X	
Elsewhere	0	0	

Now, let's consider the new applicants. As a result, the new applicants can either apply using a referrer link from the existing customers, or apply alone, and the rule is as follows:

Type	**Open Account Bonus**
Refer from current credit card users	Both Referer and new applicant get $50 after applicant spends $200 in the first month
Apply Alone	$50 after spending $200 in the first month

At the same time, some applicants may sign up aiming for the open account bonus, we call this type of customer 'bonus hunting', and the other type of customer 'spending around average'. What is more, we assume the probability of signing up using a referral link from a current credit card user p_1 = 0.2, which leaves the probability of sign up alone 1-p_1 = 0.8. Now, we assume the probability of sign up using the referrer link and being a 'spending around average' (p_2_w/o analyst = 0.9), and the probability of sign up alone and being a 'spending around average' (p_3_w/o analyst = 0.8). And we used the expected value of the average profit of all existing customers minus the cost of the sign-up bonus to generate the profits for the new customers. In order to consider the worst-case possible, we assume all 'bonus hunting' customers spend only $200 to get the $50 sign-up bonus. At the same time, we decided to use the profits in a year in the decision tree because the credit card company wants to focus on the long run, and even though the credit card company loses some signup bonus in the short run, they can generate well enough profits from new 'spending around average' customers to cover up the costs in the long run. As a result, we were able to form the following decision tree:



The credit card company is considering hiring an analyst who has the record that predicted a 'spend around average customer ' correctly at 85% of the time and a 'bonus hunting customer' correctly at 95% of the time. **The advantage of hiring an analyst is that the credit card company can reduce the probability of approving a 'bonus hunting' customer to reduce the loss**. The credit card company wants to know what is the maximum they are willing to pay for this analyst, and which bonus cashback rule they should use. Notice that the 4 profits that showed on the decision tree above are only depending on the bonus cashback rules and the probability of the good month and bad month; and the p_2 and p_3 will change if the credit card company decided to hire the analyst. We first calculate the expected profit of good month and bad month using different cashback bonus rules, and figured out the value of profits, shown below(all steps are in the tab "(New) Analyst" of the attached excel):

Yearly Profits from new customers	***i_1***	***i_2***	***i_3***	***i_4***
Profit_1	312.61	298.26	277.21	229.80
Profit_2	-102.00	-102.00	-102.00	-102.00
Profit_3	362.61	348.26	327.21	279.80
Profit_4	-52.00	-52.00	-52.00	-52.00

Then, by using the previously assumed value of p_2, and p_3, we obtained the expected value of referral and apply alone without an analyst, shown below:

W/o Analyst	**i_1**	**i_2**	**i_3**	**i_4**
Expected profits of Referral_w/o Analyst	271.15	258.23	239.29	196.62
Expected profits of Apply Alone_w/o Analyst	279.69	268.21	251.37	213.44

Now, let's consider the case when the credit card company hires the analyst(Decision Tree located in the **'(New) Analyst'** Tab of the excel sheet, not showing here because of space constraints). After computing the p_2_w/ analyst and p_3_w/ analyst in both favorable and unfavorable cases using the record of the analyst, we obtained the table of Expected Value of Referral w/ Analyst, shown below:

P(Referal_favor)=p_1 = 0.2	**i_1**	**i_2**	**i_3**	**i_4**
Expected profits of referral w/ Analyst_Favor	309.92	295.66	274.75	227.65
P(Apply Alone_favor) = 1-p_1=0.8	**i_1**	**i_2**	**i_3**	**i_4**
Expected profits of Apply Alone w/ Analyst_Favor	356.60	342.46	321.71	274.99
Expected profits of favor case w/ Analyst(P_favor = 0.73)	***347.26***	***333.10***	***312.32***	***265.52***

And the table of Expected profits of Apply Alone w/ Analyst, shown as below:

P(Referal_less_favor) =p_1=0.2	**i_1**	**i_2**	**i_3**	**i_4**
Expected profits of referral w/ Analyst_Less Favor	141.36	132.93	120.58	92.75

P(Apply Alone_less_favor) = 1-p_1=0.8	**i_1**	**i_2**	**i_3**	**i_4**
Expected profits of Apply Alone w/ Analyst_Less_Favor	108.49	102.94	94.79	76.44
Expected profits of less favor w/ Analyst(P_less_favor = 0.27)	***115.07***	***108.94***	***99.95***	***79.70***

We can see that during the first year of the approving the new customers, both Now, all we left to do is plug in the value of p_1, which we assumed to be 0.2, and calculate the Expected profits of each new customers, in the cases of whether to hire the analyst, shown below:

Expected Profits of a new customer	**i_1**	**i_2**	**i_3**	**i_4**
Expect Profit of a new customer w/o analyst	277.98	266.21	248.95	210.08
Expect Profit of a new customer w/ analyst	284.57	272.58	254.98	215.35

Like we mentioned before, the higher the total cashback that a current customer gets, the more likely he will refer this credit card to his friends. Suppose the following table represents the relationship between the probability of sending out referral link and the cashback they get:

		Spending >$1000				
Monthly probability	**Spend less than $1000**	**Total cashback = 1%**	**1%<Total cashback <=1.5%**	**1.5%<Total cashback<=2%**	**2%<& bonus cashback<=2.5 %**	**2.5%<Total cashback<=3%**
P(be Referer)	0.15%	0.17%	0.19%	0.21%	0.23%	0.25%

Then, we can calculate the number of new applicants from the referral link, and use the fixed p_1 to find the entire number of new applicants. In addition to that, we can finally calculate the expected profits from both new customers and existing customers throughout the year, shown as follows:

Yearly Data	**i_1**	**i_2**	**i_3**	**i_4**
Number of New customers	249	257	281	204
Profits from new customers w/o Analyst	69300.41	68478.34	70013.50	42855.69
Profits from new customers w/ Analyst	70943.53	70115.06	71708.83	43931.70
Maximum Willingness to pay to the analyst	1643.12	1636.72	1695.33	1076.01
Profits from existing customer(n=2000)	825219.48	796517.98	754421.55	659602.19
Total Profits w/o analyst	**894519.89**	864996.32	824435.05	702457.87
Total Profits w/ analyst	**896163.01**	866633.04	826130.38	703533.88

Conclusion:

In this project, we discussed the 4 bonus cashback rules for the credit card company, and a signup bonus, with the goal of attracting new customers, and generating more profits in the long run. In addition to that, we consider the situation where some new applicants are 'bonus hunting' and what is the maximum amount the credit card company is willing to pay for an analyst to reduce the potential loss from approving a new 'bonus hunting' applicant. The final result is showing that the best bonus cashback strategy is i_1, and the maximum that the credit card company's willingness to pay is $1643 for this year. It may seem really small, because we only assume there are only 2000 customers and calculate the profit only in one year. In the real world, for example, Chase bank has more than four million accounts and there are some additional costs of approving a bad applicant, therefore hiring an analyst may benefit them significantly. Even though this model assumed many probabilities to be fixed and the customer's data was randomly generated, there are still lots of applications using this model. In the case of a real credit card company, they should be able to observe these probabilities and customers' spendings, meaning that the only thing the credit card company needs to do to make this model usable is plug in their observed value for these variables. Based on that, they can design their own bonus cashback rules to maximize their profits, using the same approach.