HW 7 S-Mobile

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1. Develop a model to predict customer churn

<u>Adjust weight:</u>

```
actual = 1.94
oversample  = 50
1.94/50
(100-1.94)/50
mobile$sweight[mobile$churn==1]=0.0388
mobile$sweight[mobile$churn==0]=1.9612
```

<u>Build the model:</u>

```
library(dplyr)
train=filter(mobile, mobile$training==1)
test=filter(mobile, mobile$training==0)
representative = filter(mobile, mobile$representative==1)

lg0=glm(churn~.-customer-training-representative-sweight,data = train,
family="binomial",weights = sweight)
summary(lg0)

train_prob=predict(lg0,train,type = "response")
train_pred=ifelse(train_prob>=0.0194,1,0)
mean(train_pred==train$churn)

test_prob=predict(lg0,test,type = "response")
test_pred=ifelse(test_prob>=0.0194,1,0)
mean(test_pred==test$churn)
```

Training set error rate: 0.57663

Test set error rate: 0.5798291

The different is very small so overfitting is not an issue here.

Predict churn probabilities:

```
representative$rep_prob=predict(lg0,representative,type =
"response")
```

2. Use the model to understand the main drivers of churn

Key factors: changem, months, retcalls, eqpdays, creditaa

Importance:

predictor variable	dummy	AME	p-value	SD	importance
changem	0	-9.55E-06	0.0438	258.9996	0.002474019
months	0	-0.000394	0.00944	9.595614	0.003781235
retcalls	0	0.011953	0.00043	0.222183	0.002655785
eqpdays	0	2.50E-05	7.96E-06	253.9673	0.006339136
creditaa	1	-0.006847	0.02782	0.3228568	0.006847124

3. Use insights to develop actions/offers/incentives

1. Since customers who use the service more lead to lower churn rate, we can offer incentives to encourage them to use more. For example, the more minutes you use, the more you save.
2. More retention calls lead to higher churn rate. So we can decrease the calls we make to customers.
3. Longer current equipment days lead to higher churn rate. So we can offer complimentary devices(phones, routers, etc) to those who have had the current equipment for a long time.
4. Customers with higher credit rating has a much lower chance of churning. So we might want to consider expanding the market especially in high-credit customers.

variable name	predictor variable	importance	effect	Actionable?	Where in Customer life cycle?
changem	% Change in minutes of use (over 4 month period)	0.002474019	-	Y	Retention
months	# of months the customer has had service	0.003781235	-	N	Retention
retcalls	Number of calls previously made to retention team	0.002655785	+	Y	Retention
eqpdays	Number of days of the current equipment	0.006339136	+	Y	Retention
creditaa	High credit rating - aa (as opposed to medium or low)	0.006847124	-	Y	Acquisition

*Months of customer has had service is an objective measure and cannot be improved.

4. Estimate the impact of these actions/offers/incentives on the probability of churn

1. Increase minutes of use by 30% minutes in four months will lead to an average decrease of 0.0002466743 in churn rate.

```{r}
representative = filter(mobile, mobile$representative==1)
representative$rep_prob=predict(lg0,representative,type = "response")

representative$changem[representative$changem <=0] = representative$changem*0.7
representative$changem[representative$changem >0] = representative$changem*1.3
representative$revised_changem_prob = predict(lg0,representative,type='response')
mean(representative$rep_prob-representative$revised_changem_prob)
```

```
number of items to replace is not a multiple of replacement lengthnumber of items to replace
is not a multiple of replacement length[1] 0.0002466743
```

2. Decrease the number of retention calls by 30% will lead to an average decrease of 0.0001505863 in churn rate.

```{r}
representative = filter(mobile, mobile$representative==1)
representative$rep_prob=predict(lg0,representative,type = "response")
representative$retcalls = representative$retcalls*0.7
representative$revised_ret_prob = predict(lg0,representative,type='response')
mean(representative$rep_prob-representative$revised_ret_prob)
```

```
[1] 0.0001505863
```

3. Decrease the number of days of current equipment will lead to an average decrease of 0.0043214 in churn rate

```{r}
representative = filter(mobile, mobile$representative==1)
representative$rep_prob=predict(lg0,representative,type = "response")

representative$eqpdays[representative$eqpdays > 420] =0
representative$revised_eqpdays_prob = predict(lg0,representative,type='response')
mean(representative$rep_prob-representative$revised_eqpdays_prob)
```

```
[1] 0.0043214
```

5. Decide which actions/offers/incentives to target to which customers

a. Action: Give customers an opportunity to trade in their old equipment to new ones

Targeting rule: Target customers who have used their current equipment for more than 420 days

Expected churn benefit: Baseline churn: 2.43%, projected churn: 1.99%

b. Action: Decrease the number of retention calls by 30%

Targeting rule: None, affects all customers

Expected churn benefit: Baseline churn: 1.94%, projected churn: 1.92%

6. Evaluate the economics

<u>*Assumptions:</u>

1. We use the average of revenue of our target customer. Then multiple revenue by 12 months.
2. We assume the discount rate is 10%.

<u>a. Target customers who have used their current equipment for more than 420 days</u>

```
```{r}
mean(representative$revenue[representative$eqpdays > 420])
```
```

```
[1] 49.05686
```

equipement	now	year1	year2	year3	year4	year5	year6				
revenue	0	588.68232	588.68232	588.68232	588.68232	588.68232	588.68232		49.05686	588.6823	
cost	0	0	0	0	0	0	0		baseline churn	2.43%	70.84%
profit	0	588.68232	588.68232	588.68232	588.68232	588.68232	588.68232		new churn	1.99%	76.12%
active profit	100.00%	70.84%	50.18%	35.55%	25.18%	17.84%	12.64%		discount rate	0.1	
expected profit	0	417.022555	295.418778	209.274663	148.250171	105.020421	74.3964663				
present value of profit	0	379.111414	244.147751	157.231151	101.256862	65.2094188	41.9948657				
LTV	988.95146										

equipement_new	now	year1	year2	year3	year4	year5	year6				
revenue	0	588.68232	588.68232	588.68232	588.68232	588.68232	588.68232		49.05686	588.6823	
cost	0	0	0	0	0	0	0		baseline churn	2.43%	70.84%
profit	0	588.68232	588.68232	588.68232	588.68232	588.68232	588.68232		new churn	1.99%	76.12%
active profit	100.00%	76.12%	57.94%	44.11%	33.57%	25.56%	19.45%		discount rate	0.1	
expected profit	0	448.104982	341.097512	259.643426	197.640576	150.444007	114.517978				
present value of profit	0	407.368165	281.89877	195.073949	134.991173	93.4138916	64.642413				
LTV	1177.3884										
	188.4369										

Baseline annual LTV for the targeted customers is $1177.39, the projected profit for targeted customers after action is $988.95, resulting in about $188.44 increase.

<u>b. Decrease the number of retention calls by 10% to all customers</u>

```{r}
mean(representative$revenue)
```

```
[1] 59.18029
```

retention_call	now	year1	year2	year3	year4	year5	year6				
revenue	0	710.16348	710.16348	710.16348	710.16348	710.16348	710.16348		59.18029	710.1635	
cost	0	0	0	0	0	0	0		baseline churn	1.94%	76.72%
profit	0	710.16348	710.16348	710.16348	710.16348	710.16348	710.16348		new churn	1.92%	76.96%
active profit	100.00%	76.72%	58.86%	45.16%	34.64%	26.58%	20.39%		discount rate	0.1	
expected profit	0	544.837422	417.99927	320.68904	246.032631	188.756235	144.813783				
present value of profit	0	495.306747	345.453942	240.938422	168.043598	117.202771	81.7436054				
LTV	1448.6891										

retention_call_new	now	year1	year2	year3	year4	year5	year6				
revenue	0	710.16348	710.16348	710.16348	710.16348	710.16348	710.16348		59.18029	710.1635	
cost	0	0	0	0	0	0	0		baseline churn	1.94%	76.72%
profit	0	710.16348	710.16348	710.16348	710.16348	710.16348	710.16348		new churn	1.92%	76.96%
active profit	100.00%	76.96%	59.23%	45.58%	35.08%	27.00%	20.78%		discount rate	0.1	
expected profit	0	546.541814	420.61858	323.708059	249.125722	191.727156	147.553219				
present value of profit	0	496.856195	347.618661	243.206656	170.156221	119.047479	83.2899456				
LTV	1460.1752										
	11.486072										

Baseline annual LTV for the targeted customers is $1448.69, the projected profit for targeted customers after action is $1460.18, resulting in about $11.49 increase.