S-Mobile Churn

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Read in the data:

```
load("smobile_churn.Rdata")
```

Set Seed:

```
set.seed(1004)
```

Make Factor Variables:

```
rollout <- rollout %>%
mutate(customer = factor(customer),
children = factor(children),
occprof = factor(occprof),
occcler = factor(occcler),
occcrft = factor(occcrft),
occstud = factor(occstud),
occhmkr = factor(occhmkr),
occret = factor(occret),
occself = factor(occself),
travel = factor(travel),
incmiss = factor(incmiss),
agemiss = factor(agemiss),
mcycle = factor(mcycle),
creditaa = factor(creditaa),
refurb = factor(refurb)
)

smobile <- smobile %>%
mutate(customer = factor(customer),
children = factor(children),
occprof = factor(occprof),
occcler = factor(occcler),
occcrft = factor(occcrft),
occstud = factor(occstud),
occhmkr = factor(occhmkr),
occret = factor(occret),
occself = factor(occself),
travel = factor(travel),
```

```r
incmiss = factor(incmiss),
agemiss = factor(agemiss),
mcycle = factor(mcycle),
creditaa = factor(creditaa),
refurb = factor(refurb)
)
```

Split into training and test:

```r
smobile.train <- smobile %>% filter(training==1)
smobile.test <- smobile %>% filter(training==0)
```

Assignment answers

Question 1: Develop a model to predict customer churn

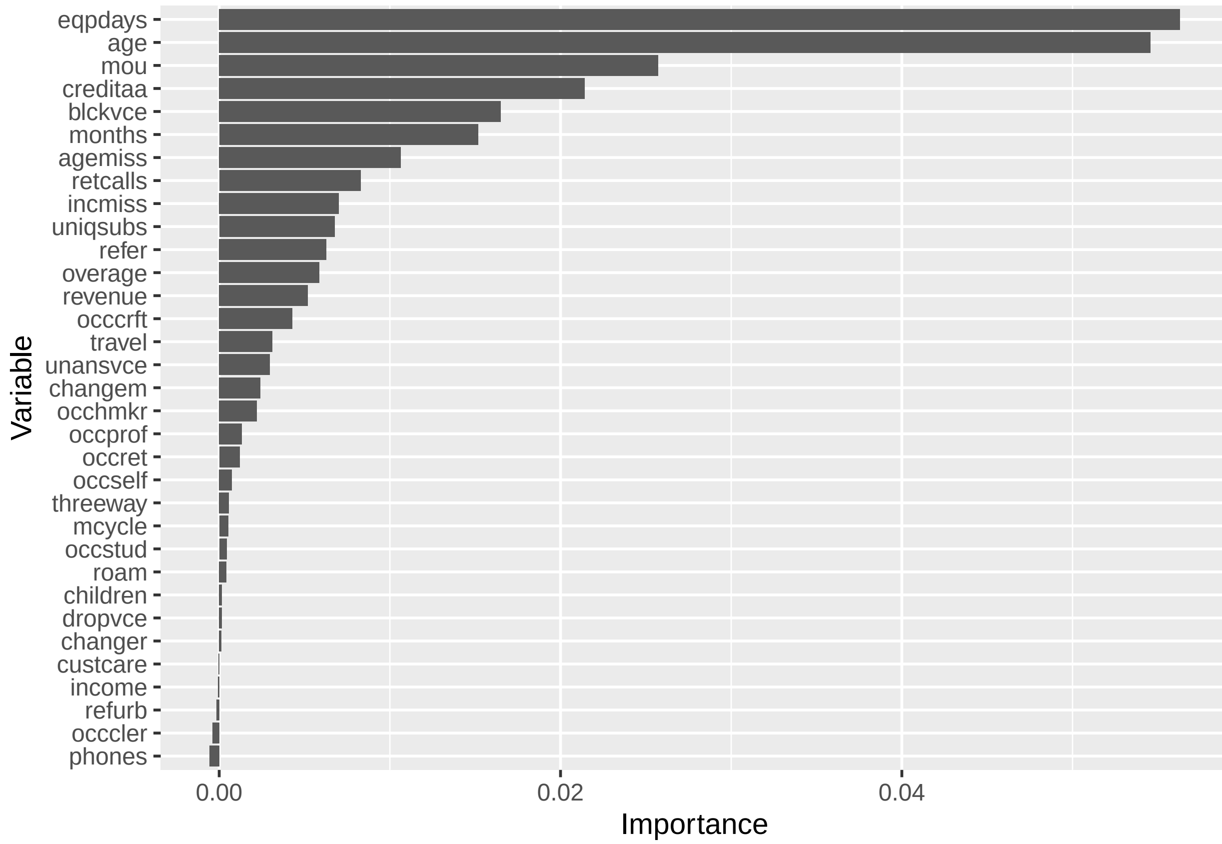
We have decided to use a logistic regression model to perform our churn predictions. Because we are hoping to understand and interpret the variables, this method works

```r
fm <- formula(churn ~ revenue + mou + overage + roam + changem +
                changer + dropvce + blckvce + unansvce +
                custcare + threeway + months + uniqsubs + phones + eqpdays +
                age + agemiss + children + creditaa + refurb + occprof + occcler
                + occcrft + occstud + occhmkr + occret + occself + travel +
                retcalls + refer + incmiss + income + mcycle)

#LR

lr <- glm(fm, family=binomial, data=smobile.train)


#LR_Prediction_Rollout

rollout <- rollout %>%
  mutate(churn_lr = predict(lr, newdata=rollout, type="response"))
```

Question 2: Use the model to understand the main drivers of churn. Report key factors that predict churn and their importance.

The key factors that are showing up as important variables are days that someone has had equipment, age, mean monthly minutes of use, credit rating, months and mean number of blocked voice calls. However, age is an odd one because if an age is 0 it just means the age is not available. Therefore below, we also run a model on those who only have age inputted and it still appears as an important predictor variable so we conclude the curve shown in the pardepplot is relevant.

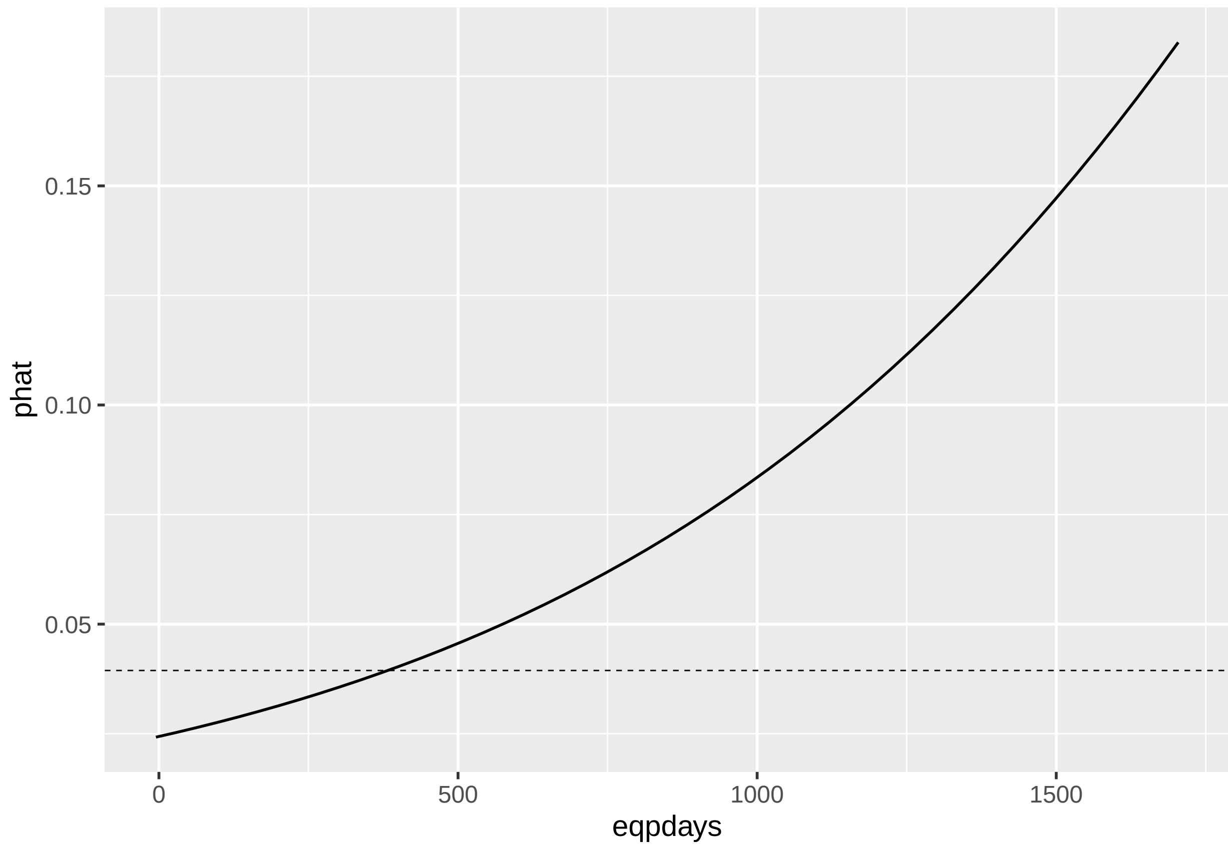
```r
#LR

varimpplot(lr, target="churn")
```



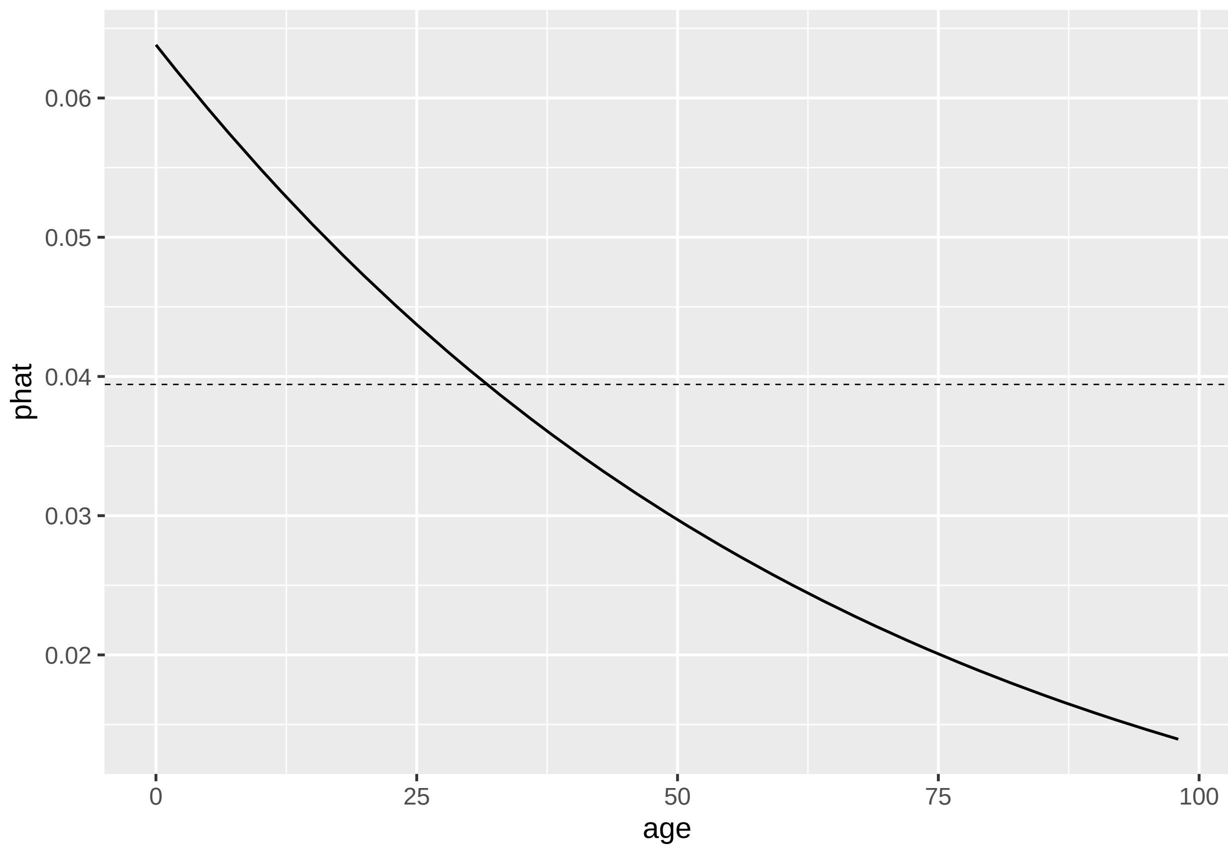

```r
smobile.train %>%
  summarize(perc.churn = mean(churn==1))
```

```
# A tibble: 1 x 1
  perc.churn
       <dbl>
1     0.0394
```

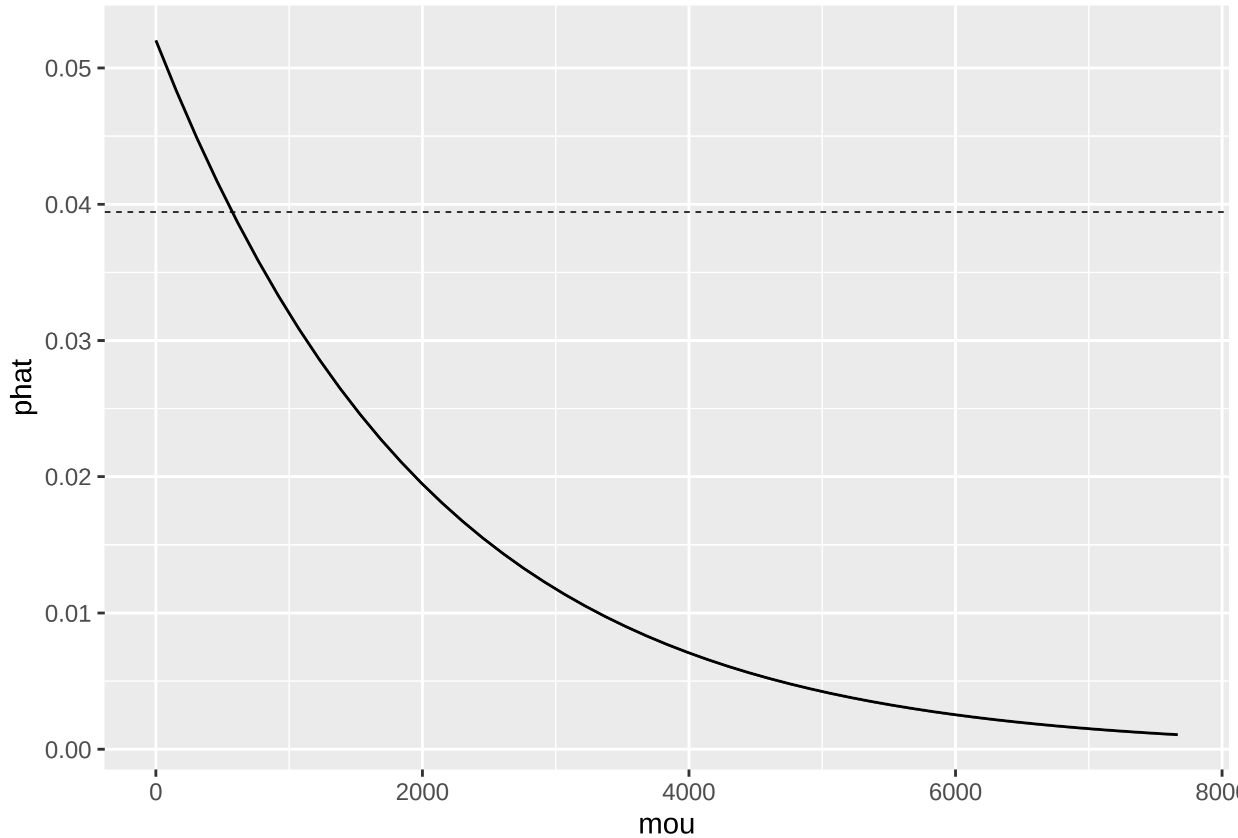
```r
perc.churn <- 0.03942857

pardepplot(lr, pred.var="eqpdays", data=smobile.train, hline=perc.churn)
```



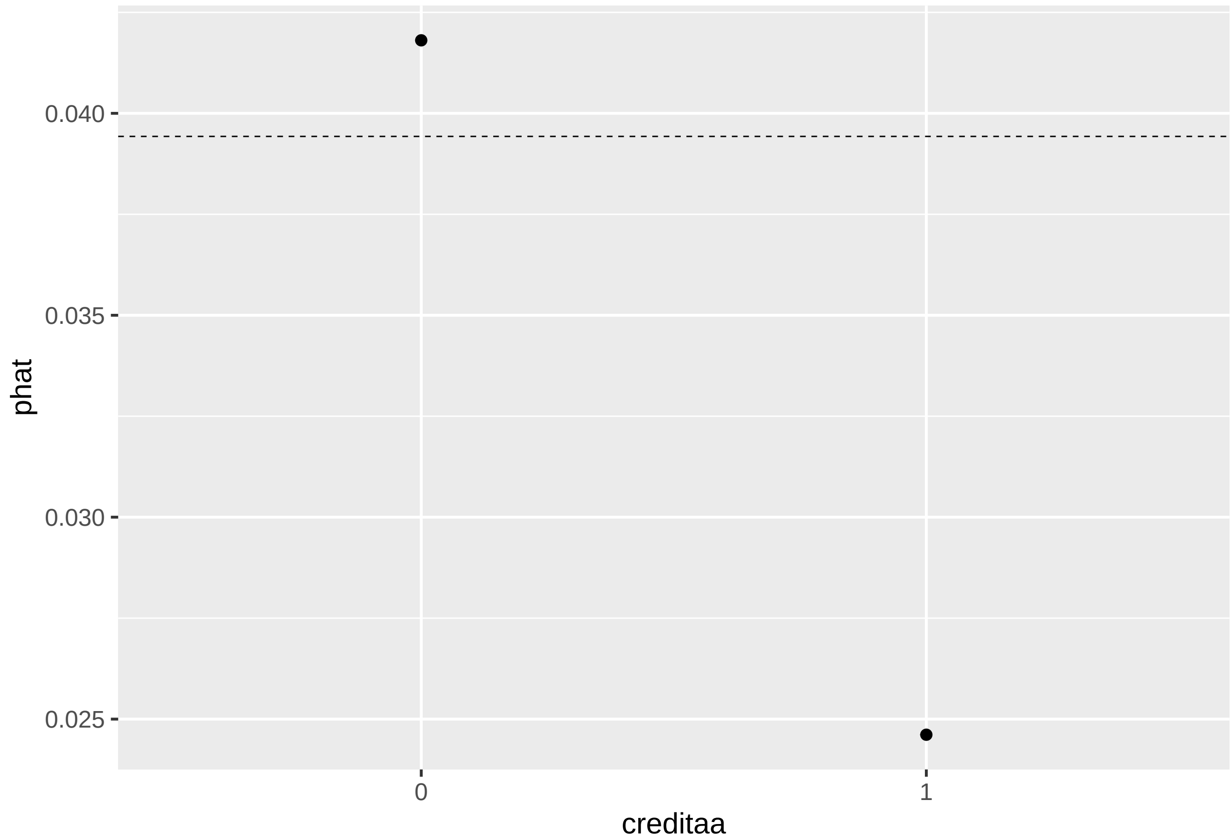

```r
pardepplot(lr, pred.var="age", data=smobile.train, hline=perc.churn)
```



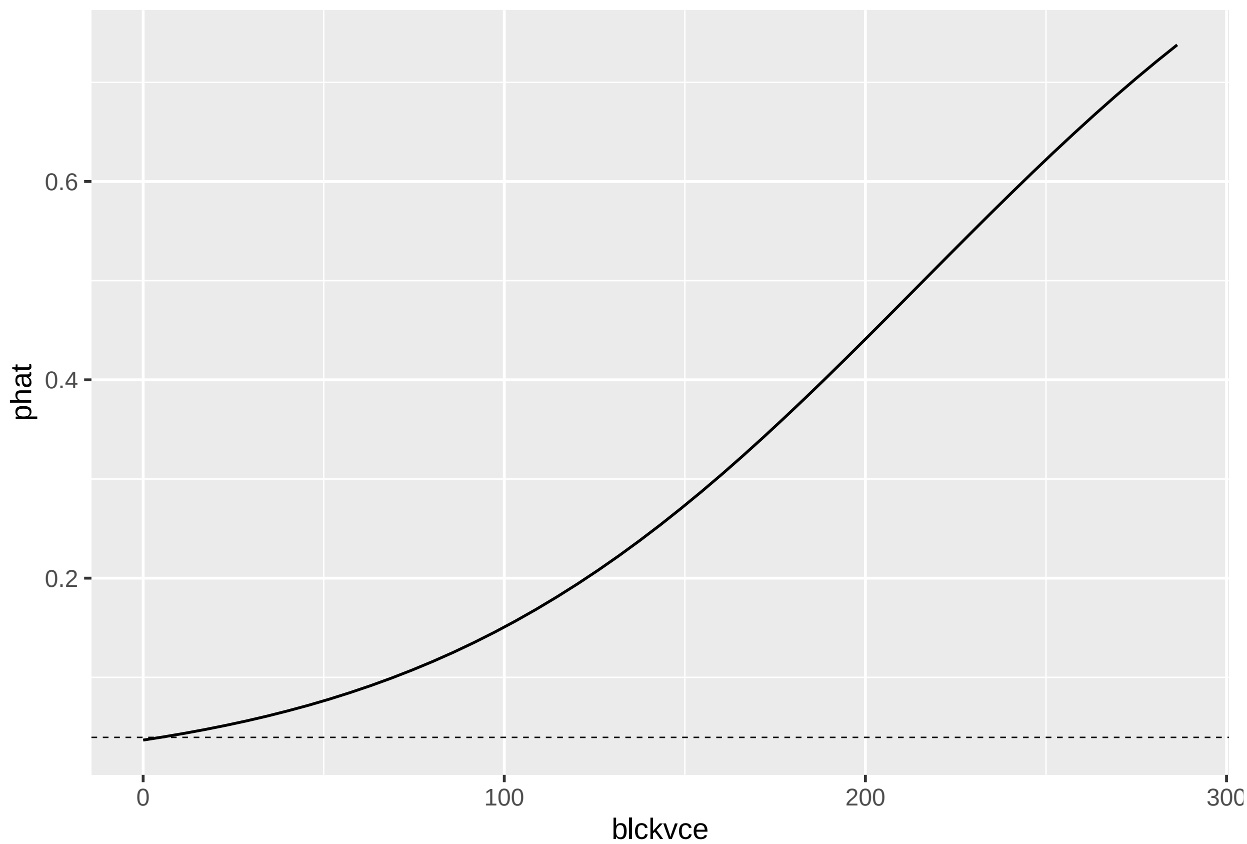

```r
pardepplot(lr, pred.var="mou", data=smobile.train, hline=perc.churn)
```



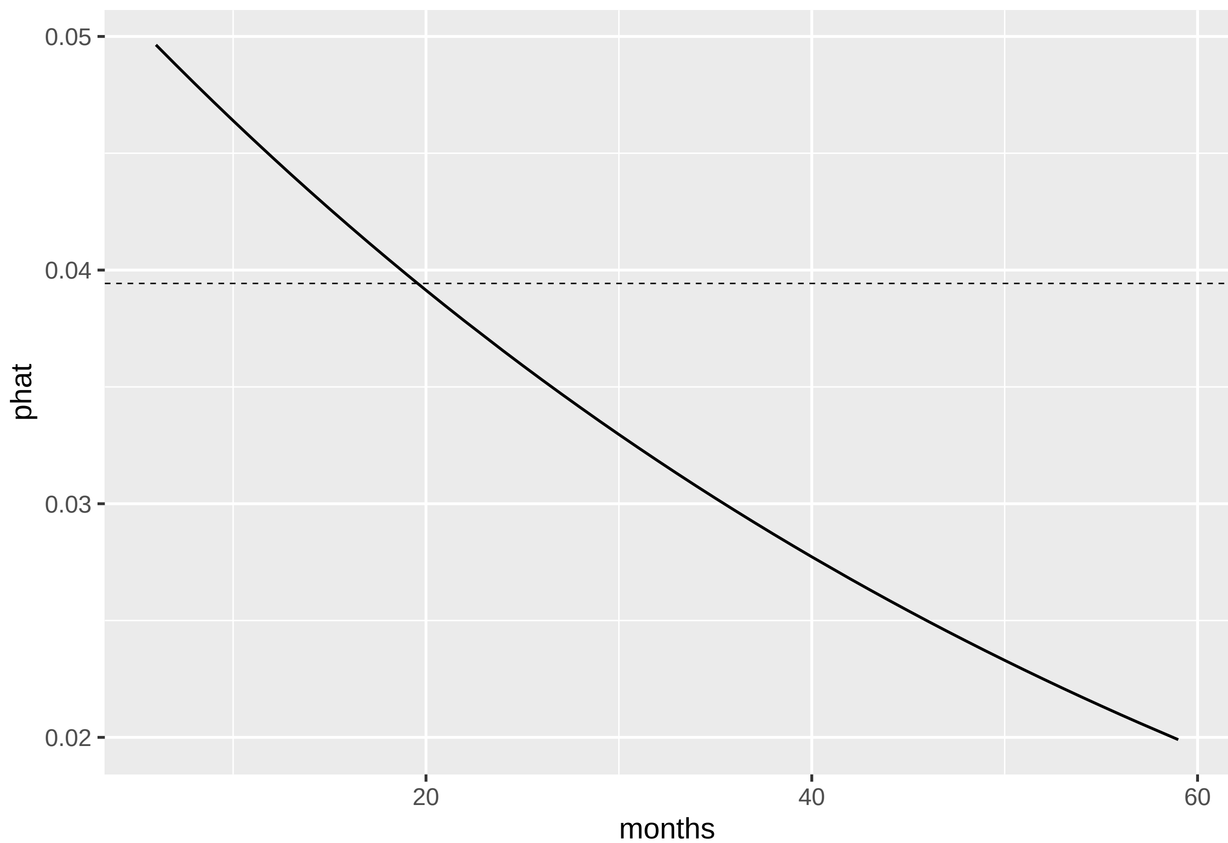

```
pardepplot(lr, pred.var="creditaa", data=smobile.train, hline=perc.churn)
```




```
pardepplot(lr, pred.var="blckvce", data=smobile.train, hline=perc.churn)
```




```
pardepplot(lr, pred.var="months", data=smobile.train, hline=perc.churn)
```

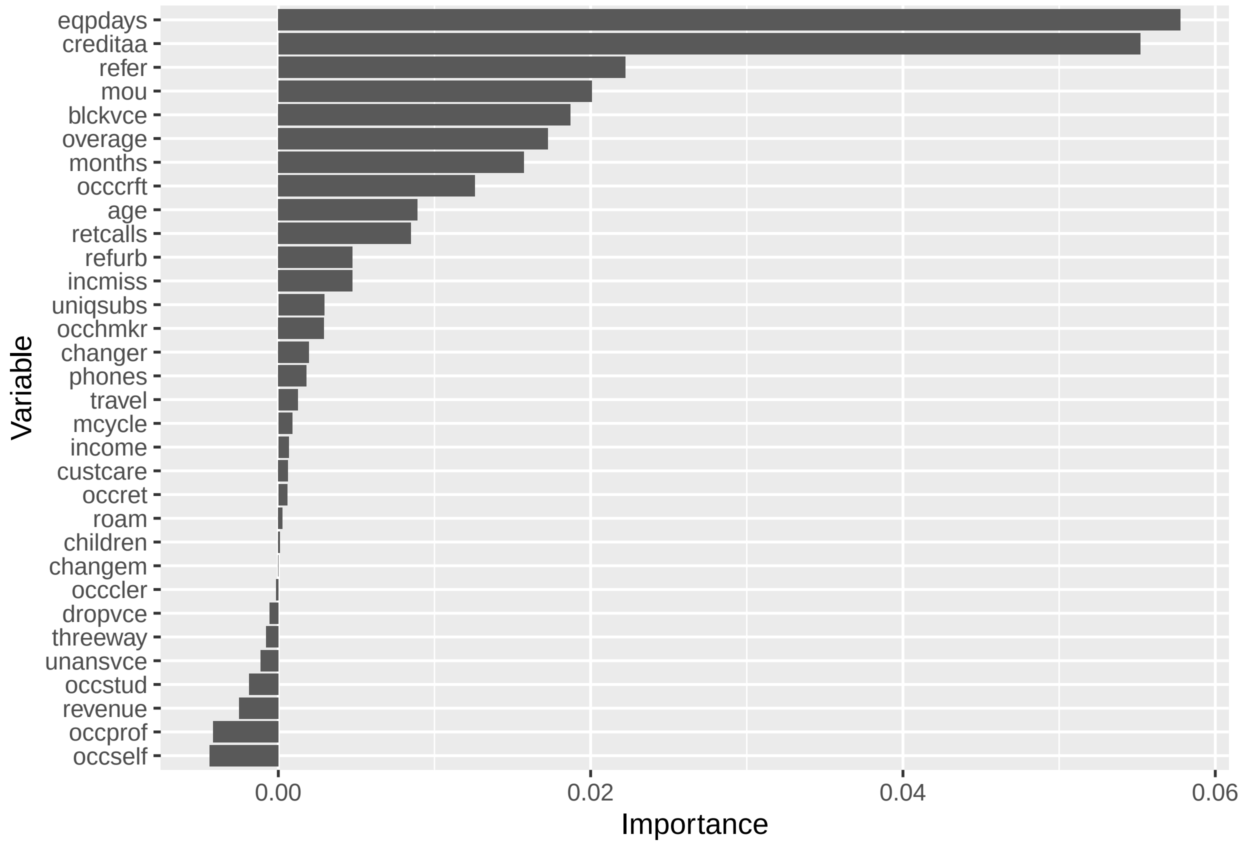



```r
summary(lr)
```

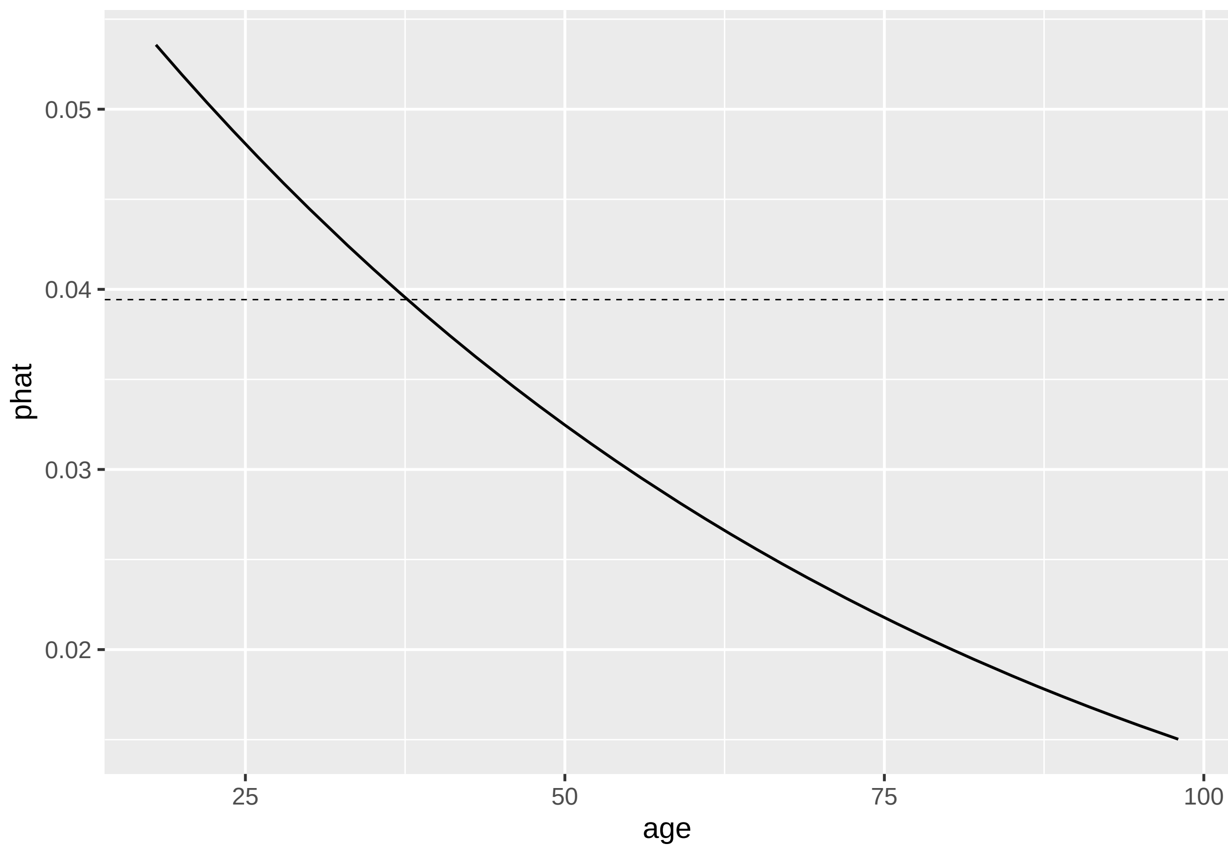
```

Call:
glm(formula = fm, family = binomial, data = smobile.train)

Coefficients:
              Estimate Std. Error z value Pr(>|z|)    
(Intercept) -3.0790100  0.3927087  -7.840 4.49e-15 ***
revenue      0.0023081  0.0026485   0.871 0.383512    
mou         -0.0005223  0.0002282  -2.289 0.022082 *  
overage      0.0012991  0.0008707   1.492 0.135689    
roam         0.0011300  0.0091256   0.124 0.901454    
changem     -0.0001456  0.0003150  -0.462 0.644007    
changer     -0.0011700  0.0020578  -0.569 0.569664    
dropvce      0.0003786  0.0088781   0.043 0.965982    
blckvce      0.0157017  0.0039198   4.006 6.18e-05 ***
unansvce     0.0013042  0.0021420   0.609 0.542628    
custcare    -0.0059974  0.0168837  -0.355 0.722428    
threeway    -0.0233032  0.0328647  -0.709 0.478284    
months      -0.0181096  0.0107572  -1.683 0.092281 .  
uniqsubs     0.1638001  0.0636055   2.575 0.010017 *  
phones       0.0311120  0.0708582   0.439 0.660607    
eqpdays      0.0013142  0.0003807   3.452 0.000557 ***
age         -0.0162599  0.0068316  -2.380 0.017308 *  
```

```
agemiss1    -0.4348835  0.3683478  -1.181 0.237749
children1   -0.0434708  0.1643164  -0.265 0.791352
creditaa1   -0.5547280  0.2264624  -2.450 0.014304 *
refurb1      0.0265338  0.1917298   0.138 0.889931
occprof1     0.2074751  0.1891593   1.097 0.272717
occcler1    -0.0641170  0.5219908  -0.123 0.902240
occcrft1     0.5967373  0.3194304   1.868 0.061744 .
occstud1     0.2242857  0.7366422   0.304 0.760770
occhmkr1     0.8009078  0.7505756   1.067 0.285946
occret1      0.1974465  0.6198244   0.319 0.750066
occself1     0.3147290  0.4757480   0.662 0.508262
travel1     -0.1672166  0.3064518  -0.546 0.585304
retcalls     0.4969203  0.2733701   1.818 0.069101 .
refer       -0.5650638  0.3783102  -1.494 0.135267
incmiss1     0.1611407  0.3196411   0.504 0.614170
income      -0.0122394  0.0354409  -0.345 0.729833
mcycle1     -0.1849379  0.5972747  -0.310 0.756838
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 2325.7  on 6999  degrees of freedom
Residual deviance: 2245.4  on 6966  degrees of freedom
AIC: 2313.4

Number of Fisher Scoring iterations: 6
```

```r
smobile.train.agefiltered <- smobile.train %>%
  filter(age>0)

fm2 <- formula(churn ~ revenue + mou + overage + roam + changem +
                changer + dropvce + blckvce + unansvce +
                custcare + threeway + months + uniqsubs + phones + eqpdays +
                age + children + creditaa + refurb + occprof + occcler
                + occcrft + occstud + occhmkr + occret + occself + travel +
                retcalls + refer + incmiss + income + mcycle)

lr2 <- glm(fm2, family=binomial, data=smobile.train.agefiltered)


varimpplot(lr2, target="churn", data=smobile.train.agefiltered)
```




```
pardepplot(lr2, pred.var="age", data=smobile.train.agefiltered, hline=perc.churn)
```



Question 3: Use insights to develop actions/offers/incentives

Below, we developed some ideas based on the results for variable importance, and which variables were statistically significant. We also used trends in the pardepplots to look at cutoff points and specific pieces of the population that would make sense to target.

Equipment days - People who have an older equipment churn more based on the pardepplots.By targeting people who have already purchased phones you'd be targeting them in the retention stage. You could offer a promotion that if they've had their device for over a year, you'll get them a new device.

Blocking voice calls – we are assuming the blocked calls here as spam. More spam calls causes more churn according to pardepplot. If you are able to implement a spam blocker for everyone, you could potentially reduce churn for the entire population - create spam filters to ensure the maximum amount of spam calls anyone receives is not above 10. This would be in the retention phase

Age - younger people generally churn more than older people according to the pardepplot. While age itself is not necessarily actionable, you could target older users as they are less likely to churn - this would be in the acquisition phase of customer lifecycle. You could provide these users with a discount to join. This would be harder to measure longer term and age did not come up as high on importance scale when taking out those with no age documented, so we decided not to evaluate this.

Finally, we could look at months in service. According to the pardepplots, the longer someone has subscribed to our service, the less likely they are to churn. One could target new users with 20 months or less to stay past 2 years via a new member discount up until the point where churn becomes less likely. Because we couldn't combine age in the previous one but know it's a powerful predictor, we also would limit this group to age 35 or less.

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

Option 1: Provide new equipment to everyone who has more than 1 year old equipment or who has refurbished equipment. Yearly churn with those having older than 365 day old equipment is 44.65%.

Ideally, we'd conduct a true experiment to understand how churn was impacted. To do this, we'd have to get a sample of around 1,000 if we wanted .03 precision at 95% confidence. To conduct the experiment, you'd have to filter individuals who have a phone older than 365 and randomly select individuals to get a brand new phone while others keep their phone. To conduct the experiment you'd need to give these randomly individuals a new phone and measure over a set time period how many of these individuals churned. For this experiment, you'd need a long time to understand the effects as you'd want to understand how churn changes if you gave them a new phone every 365 days. If you conducted an experiment over a few months, you may understand their short term churn reduction but likely over the longer term this could change as the device constantly gets older.

While we recognize a true experiment would be the proper method, we can simulate effects below for giving individuals who have hit 365 days with their device new phones. Below you can see everyone who has an older device receiving new phones would reduce the churn rate from 44.65% to 23.82%. While this is a large leap, there is reason to be skeptical of this number - individuals are not randomly assigned to keep their phones for a certain number of times, there are drivers like resistance to change or economic considerations that may influence how long someone has a phone - economic considerations could potentially influence someone to drop their plan regardless of how old their phone is. For the purposes of the assignment we will assume instead we ran an experiment and instead of dropping all the way to 23.82% the results indicated churn dropped to 30% (mitigating some of the confounding effects found in the checklist).

```r
ss.proportion(.03)
```

```
[1] 1068
```

```r
eqpdays.simulation.before <- rollout %>%
  filter(eqpdays>365)



baseline.churn <- predict(lr, newdata = eqpdays.simulation.before, type="response") %>%
  mean()


yearly.baseline.churn <- 1-((1-baseline.churn)^12)

yearly.baseline.churn
```

```
[1] 0.4464716
```

```r
eqpdays.simulation.after <- rollout %>%
  filter(eqpdays>365) %>%
  mutate(eqpdays = 0)

projected.churn <- predict(lr, newdata = eqpdays.simulation.after, type="response") %>%
  mean()
```

```r
yearly.projected.churn <- 1-((1-projected.churn)^12)

yearly.projected.churn
```

```
[1] 0.2381629
```

```r
##see explanation above

yearly.adjusted.churn <-- .3


##info for profitability analysis

avg.revenue <- mean(eqpdays.simulation.before$revenue)

avg.revenue
```

```
[1] 49.96905
```

Option 2: Create spam blocker to limit spam calls for those with more than one blocked voice call. The churn for this group originally is 38.1%.

Ideally, we'd conduct a true experiment to understand how churn was impacted. To do this, we'd have to get a sample of around 1,000 if we wanted .03 precision at 95% confidence. To conduct the experiment, you'd have to filter those blocking at least one call (again we are assuming the blocked calls are spam). To conduct the experiment you'd need to randomly assign a group of people to get a spam blocker while the others continue to receive the spam calls and measure over a set period of time how this impacts the churn rate for the new action. While in theory this would be the right method, it may be difficult to get larger sample sizes for those receiving large amounts of spam calls.

While we recognize a true experiment would be the proper method, we can simulate effects below for giving individuals who block at least one voice call with their device new phones. Below you can see everyone who has an older device receiving new phones would reduce the churn rate from 38.1% to 35.2%. To go through the checklist, even though they weren't randomly assigned to get spam calls, there isn't necessarily a rhyme or reason why one person might get more spam calls than another person. Building on this, perhaps they could just be sending out their phone number more often or their phone number is publicly available, this seems more of an anomaly than the rule. Either way, it doesn't seem like a driver would have influence on churn more than the actual variable itself. Therefore, this number seems fairly realistic.

```r
blckvce.simulation.before <- rollout %>%
  filter(blckvce>0)



baseline.churn2 <- predict(lr, newdata = blckvce.simulation.before, type="response") %>%
  mean()


yearly.baseline.churn2 <- 1-((1-baseline.churn2)^12)

yearly.baseline.churn2
```

```
[1] 0.3806266
```

```r
blckvce.simulation.after <- rollout %>%
  filter(blckvce>0) %>%
  mutate(blckvce=0)

projected.churn <- predict(lr, newdata = blckvce.simulation.after, type="response") %>%
  mean()


yearly.projected.churn2 <- 1-((1-projected.churn)^12)

yearly.projected.churn2
```

```
[1] 0.3527663
```

```r
#Average Customer Revenue

avg.revenue2 <- mean(blckvce.simulation.before$revenue)

avg.revenue2
```

```
[1] 64.28371
```

Option 3: During the initial phases following customer purchase we could target those with fewer months active to stay through a discount offered to a point where churn rate drops more substantially. Specifically for this offer, we'd want to target those who have been using the service for less than 20 months and who are under 35 as their churn is higher and we want to convince them to stay.

For this option, we will hypothetically choose to conduct an "experiment" as manipulating current data to reflect this does not seem feasible. As a baseline, the churn rate for this group is 37.3 percent. To do this we would conduct an a/b test and randomly select roughly 1000 individuals (based on reasoning previously) who have used the service for less than 20 months and are younger than 35 to give an offer to to stay past 24 months. This experiment would likely last over a period of 6 months or more to understand the true effects on churn. For the sake of the assignment, we will assume the result is a success! And reduce the churn rate to 25%. This is an estimate based on viewing the difference in average predicted churn rate for those with 0-20 months compared with those 24+ months in the pardepplots.

```r
months.simulation.before <- rollout %>%
  filter(months<20, age<35)



baseline.churn3 <- predict(lr, newdata = months.simulation.before, type="response") %>%
  mean()


yearly.baseline.churn3 <- 1-((1-baseline.churn3)^12)

yearly.baseline.churn3
```

```
[1] 0.41666
```

```r
#Average Customer Revenue

avg.revenue3 <- mean(months.simulation.before$revenue)

avg.revenue3
```

```
[1] 61.84951
```

Question 5: Decide which actions/offers/incentives to target to which customers

1) Option 1, giving everyone a new device who has a device older than 365 days (filtering only those with eqpdays > 365) and who's churn rate is predicted as above average the average .039.

2) Option 2, employing a spam call blocker to all those blocking more than 1 voice call (filtering blckvce > 0) and who's churn rate is predicted as above the average .039.

3) Option 3, offering a promotion (financial/bill discount) to those who have been subscribed/using the offering for less than 20 months (months <21), are younger than the age of 35 (age <35), and have an above average churn prediction (above .039). The length of the promotion would last until they hit 2 years or 24 months.

We will evaluate the profitability in the excel tables following this for question 6.

Option 1: Provide new equipment to everyone who has more than 1 year old equipment or who has refurbished equipment. Yearly churn with those having older than 365 day old equipment is 44.65%.

	Start of LTV	Yr 1	Yr 2	Yr 3	Yr 4	Yr 5	Yr 6	Yr 7	Yr 8	Yr 9	Yr 10	
Average Customer Revenue	$ -	$ 599.64	$ 629.62	$ 661.10	$ 694.16	$ 728.87	$ 765.31	$ 803.57	$ 843.75	$ 885.94	$ 930.24	
Incentive/ Offer Cost	$ -											
COGS/ SG&A	$ -	$ 494.36	$ 519.08	$ 545.03	$ 572.28	$ 600.90	$ 630.94	$ 662.49	$ 695.61	$ 730.39	$ 766.91	
Profit	$ -	$ 105.28	$ 110.54	$ 116.07	$ 121.87	$ 127.97	$ 134.37	$ 141.09	$ 148.14	$ 155.55	$ 163.32	
Probability of being active at end of period	100.0%	55.4%	30.7%	17.0%	9.4%	5.2%	2.9%	1.6%	0.9%	0.5%	0.3%	
Average prob of being active in period	100.0%	77.7%	43.0%	23.8%	13.2%	7.3%	4.1%	2.2%	1.2%	0.7%	0.4%	
Expected Profit	$ -	$ 81.80	$ 47.58	$ 27.68	$ 16.10	$ 9.37	$ 5.45	$ 3.17	$ 1.84	$ 1.07	$ 0.62	
Expected Profit Present Value	$ -	$ 78.00	$ 41.25	$ 21.81	$ 11.53	$ 6.10	$ 3.23	$ 1.71	$ 0.90	$ 0.48	$ 0.25	**$ 165.25**

For this offer, it would need to cost less than $30.32 dollars per person over the lifetime for the offer to make sense, or $3.32 per year. Likely, this might not be feasible if we are giving everyone a new phone every year even if we are targeting only those with churn rates above average.

$ 30.32

Assumptions:
Yearly revenue growth = 5%
Yearly cost growth = 5%
Baseline Yearly churn = 44.6
Financial discount rate = 10%

We are also assuming costs are roughly 70% of average revenue per person, we kept these consistent across customer sets

	Start of LTV	Yr 1	Yr 2	Yr 3	Yr 4	Yr 5	Yr 6	Yr 7	Yr 8	Yr 9	Yr 10	
Average Customer Revenue	$ -	$ 599.64	$ 629.62	$ 661.10	$ 694.16	$ 728.87	$ 765.31	$ 803.57	$ 843.75	$ 885.94	$ 930.24	
Incentive/ Offer Cost	$ -											
COGS/ SG&A	$ -	$ 494.36	$ 519.08	$ 545.03	$ 572.28	$ 600.90	$ 630.94	$ 662.49	$ 695.61	$ 730.39	$ 766.91	
Profit	$ -	$ 105.28	$ 110.54	$ 116.07	$ 121.87	$ 127.97	$ 134.37	$ 141.09	$ 148.14	$ 155.55	$ 163.32	
Probability of being active at end of period	100.0%	70.0%	38.8%	21.5%	11.9%	6.6%	3.7%	2.0%	1.1%	0.6%	0.3%	
Average prob of being active in period	100.0%	85.0%	54.4%	30.1%	16.7%	9.2%	5.1%	2.8%	1.6%	0.9%	0.5%	
Expected Profit	$ -	$ 89.49	$ 60.12	$ 34.97	$ 20.34	$ 11.83	$ 6.88	$ 4.00	$ 2.33	$ 1.36	$ 0.79	
Expected Profit Present Value	$ -	$ 85.32	$ 52.12	$ 27.56	$ 14.57	$ 7.71	$ 4.08	$ 2.16	$ 1.14	$ 0.60	$ 0.32	**$ 195.57**

Assumptions:
Yearly revenue growth = 5%
Yearly cost growth = 5%
Yearly churn = 30
Financial discount rate = 10%

Option 2: Create spam blocker to limit spam calls for those with more than one blocked voice call. The churn for this group originally is 38.1%.

	Start of LTV	Yr 1	Yr 2	Yr 3	Yr 4	Yr 5	Yr 6	Yr 7	Yr 8	Yr 9	Yr 10	
Average Customer Revenue	$ -	$ 771.36	$ 809.93	$ 850.42	$ 892.95	$ 937.59	$ 984.47	$1,033.70	$1,085.38	$1,139.65	$1,196.63	
Incentive/ Offer Cost	$ -											
COGS/ SG&A	$ -	$ 494.36	$ 519.08	$ 545.03	$ 572.28	$ 600.90	$ 630.94	$ 662.49	$ 695.61	$ 730.39	$ 766.91	
Profit	$ -	$ 277.00	$ 290.85	$ 305.39	$ 320.66	$ 336.70	$ 353.53	$ 371.21	$ 389.77	$ 409.26	$ 429.72	
Probability of being active at end of period	100.0%	61.9%	38.4%	23.8%	14.7%	9.1%	5.6%	3.5%	2.2%	1.3%	0.8%	
Average prob of being active in period	100.0%	81.0%	50.2%	31.1%	19.2%	11.9%	7.4%	4.6%	2.8%	1.8%	1.1%	
Expected Profit	$ -	$ 224.29	$ 145.87	$ 94.87	$ 61.70	$ 40.13	$ 26.10	$ 16.97	$ 11.04	$ 7.18	$ 4.67	
Expected Profit Present Value	$ -	$ 213.85	$ 126.44	$ 74.76	$ 44.20	$ 26.13	$ 15.45	$ 9.14	$ 5.40	$ 3.19	$ 1.89	$ 520.44

For this offer, it would need to cost less than approximately 17.94 per person over the lifetime for this action of employing a spam blocker to be profitable, or 1.79 per year. This may be feasible, particularly if we only target those who's churn is greater than the average.

Assumptions:
Yearly revenue growth = 5% 61.94
Yearly cost growth = 5%
Baseline Yearly churn = 38.06
Financial discount rate = 10%

$ 17.49

	Start of LTV	Yr 1	Yr 2	Yr 3	Yr 4	Yr 5	Yr 6	Yr 7	Yr 8	Yr 9	Yr 10	
Average Customer Revenue	$ -	$ 771.36	$ 809.93	$ 850.42	$ 892.95	$ 937.59	$ 984.47	$1,033.70	$1,085.38	$1,139.65	$1,196.63	
Incentive/ Offer Cost	$ -											
COGS/ SG&A	$ -	$ 494.36	$ 519.08	$ 545.03	$ 572.28	$ 600.90	$ 630.94	$ 662.49	$ 695.61	$ 730.39	$ 766.91	
Profit	$ -	$ 277.00	$ 290.85	$ 305.39	$ 320.66	$ 336.70	$ 353.53	$ 371.21	$ 389.77	$ 409.26	$ 429.72	
Probability of being active at end of period	100.0%	64.7%	40.1%	24.8%	15.4%	9.5%	5.9%	3.7%	2.3%	1.4%	0.9%	
Average prob of being active in period	100.0%	82.4%	52.4%	32.5%	20.1%	12.5%	7.7%	4.8%	3.0%	1.8%	1.1%	
Expected Profit	$ -	$ 228.15	$ 152.44	$ 99.14	$ 64.48	$ 41.94	$ 27.27	$ 17.74	$ 11.54	$ 7.50	$ 4.88	
Expected Profit Present Value	$ -	$ 217.53	$ 132.13	$ 78.12	$ 46.19	$ 27.31	$ 16.15	$ 9.55	$ 5.64	$ 3.34	$ 1.97	$ 537.94

Assumptions:
Yearly revenue growth = 5%
Yearly cost growth = 5% 64.72
Yearly churn = 35.28
Financial discount rate = 10%

Option 3, offering a promotion to those who have been subscribed/using the offering for less than 20 months and younger than the age of 35. The length of the promotion would last until they hit 2 years or 24 months.

	Start of LTV	Yr 1	Yr 2	Yr 3	Yr 4	Yr 5	Yr 6	Yr 7	Yr 8	Yr 9	Yr 10	
Average Customer Revenue	$ -	$ 742.20	$ 779.31	$ 818.28	$ 859.19	$ 902.15	$ 947.26	$ 994.62	$1,044.35	$1,096.57	$1,151.40	
Incentive/ Offer Cost	$ -											
COGS/ SG&A	$ -	$ 494.36	$ 519.08	$ 545.03	$ 572.28	$ 600.90	$ 630.94	$ 662.49	$ 695.61	$ 730.39	$ 766.91	
Profit	$ -	$ 247.84	$ 260.23	$ 273.24	$ 286.91	$ 301.25	$ 316.31	$ 332.13	$ 348.74	$ 366.17	$ 384.48	
Probability of being active at end of period	100.0%	58.3%	34.0%	19.8%	11.6%	6.8%	3.9%	2.3%	1.3%	0.8%	0.5%	
Average prob of being active in period	100.0%	79.2%	46.2%	26.9%	15.7%	9.2%	5.3%	3.1%	1.8%	1.1%	0.6%	
Expected Profit	$ -	$ 196.20	$ 120.17	$ 73.60	$ 45.08	$ 27.61	$ 16.91	$ 10.36	$ 6.34	$ 3.88	$ 2.38	
Expected Profit Present Value	$ -	$ 187.07	$ 104.16	$ 57.99	$ 32.29	$ 17.98	$ 10.01	$ 5.57	$ 3.10	$ 1.73	$ 0.96	$ 420.87

For this offer, it would need to cost less than approximately $85.61 per person in this group over the lifetime of the customer. This is realistic and feasible as the offer will only be for a set period of time (year 1 and 2) and only target those with predicted churn greater than the average.

Assumptions:
Yearly revenue growth = 5% 58.33
Yearly cost growth = 5%
Baseline Yearly churn = 41.67
Financial discount rate = 10%

$ 86.51

	Start of LTV	Yr 1	Yr 2	Yr 3	Yr 4	Yr 5	Yr 6	Yr 7	Yr 8	Yr 9	Yr 10	
Average Customer Revenue	$ -	$ 742.20	$ 779.31	$ 818.28	$ 859.19	$ 902.15	$ 947.26	$ 994.62	$1,044.35	$1,096.57	$1,151.40	
Incentive/ Offer Cost	$ -											
COGS/ SG&A	$ -	$ 494.36	$ 519.08	$ 545.03	$ 572.28	$ 600.90	$ 630.94	$ 662.49	$ 695.61	$ 730.39	$ 766.91	
Profit	$ -	$ 247.84	$ 260.23	$ 273.24	$ 286.91	$ 301.25	$ 316.31	$ 332.13	$ 348.74	$ 366.17	$ 384.48	
Probability of being active at end of period	100.0%	75.0%	43.7%	25.5%	14.9%	8.7%	5.1%	3.0%	1.7%	1.0%	0.6%	
Average prob of being active in period	100.0%	87.5%	59.4%	34.6%	20.2%	11.8%	6.9%	4.0%	2.3%	1.4%	0.8%	
Expected Profit	$ -	$ 216.86	$ 154.51	$ 94.63	$ 57.96	$ 35.50	$ 21.74	$ 13.32	$ 8.16	$ 4.99	$ 3.06	
Expected Profit Present Value	$ -	$ 206.77	$ 133.93	$ 74.57	$ 41.52	$ 23.12	$ 12.87	$ 7.17	$ 3.99	$ 2.22	$ 1.24	$ 507.39

$ 86.51

Assumptions:
Yearly revenue growth = 5%
Yearly cost growth = 5% 77
Yearly churn = 25
Financial discount rate = 10%