

# LTV Unwired: Exploring Lyft Drivers

A comprehensive overview

# Drivers Lifetime Value (LTV)

SF Rideshare/ Regular Rates	UBERX	LYFT	TAXI
Base Fare	\$3.00	<b>\$2.00</b>	\$3.50
Per Minute (waiting- only for taxis)	\$0.30	<b>\$0.22</b>	\$0.55
Per Mile	\$1.50	<b>\$1.15</b>	\$2.75
Service Fee		<b>\$1.75</b>	
Min/Max	<b>\$5-\$400</b>		

“Present value of future cash flows expected from drivers over the entire projected lifetime of a driver”

$$\text{LTV for a Driver} = \sum_{m=0} \frac{\text{Margin}_m \text{Prob(Active)}_m}{(1 + WACC)^m}$$

WACC is the discount rate\*

# The math model: LTV of Drivers

- The LTV over the next 12 months can be divided as the sum of LTV for each month for the next 12 months:

$$L = V_1 + V_2 + \dots + V_{12}$$

- At each of the month, we can simply say

LTV= (Cash flow given the Driver Retains) \* (Probability of Retention)

\*  $\{m\}$  is a time period, e.g. the first month ( $\{m\}=1$ ), the second month ( $\{m\}=2$ )

\*  $\{n\}$  is the total number of periods the driver will stay before he/she finally churns

\* Prob(Active) $_m$  is the retention rate/possibility in month  $m$

\* Margin is the profit (cash flow) the driver will contribute in the month  $m$

\* WACC is the discount rate

Here we assume that WACC is constant in the formula

we look at the existing cash flows of each driver

Table 1

Cash flow	2016-03-28	2016-03-29	2016-03-30	2016-03-31	2016-04-01	2016-04-02	2016-04-03	2016-04-04	2016-04-05
002be0ff dc997bd 5c50703 158b7c2		\$246.61		\$365.60	\$338.02	\$220.56			\$346.43
007f038 9f9c7b0 3ef9709 8422f90		\$56.59							
02e440f 6c20920 6375833 cef02e0				\$320.34		\$214.78		\$34.57	
0938ed7 63cb312 9ae6360 7aaf69d			\$239.09	\$172.52	\$188.53			\$107.39	\$119.49

# Variables Selected Included to calculate LTV (% Retention in the next period)



Profile-related

Tenure (Time with Lyft)  
Prime vs. Regular



Behavior-related

**Recency [Days]**

Ride distance

Ride Duration

Ride Prime Time %

Response Time

**Frequency (# rides per month)**

**Monetary (Cash Flow)**

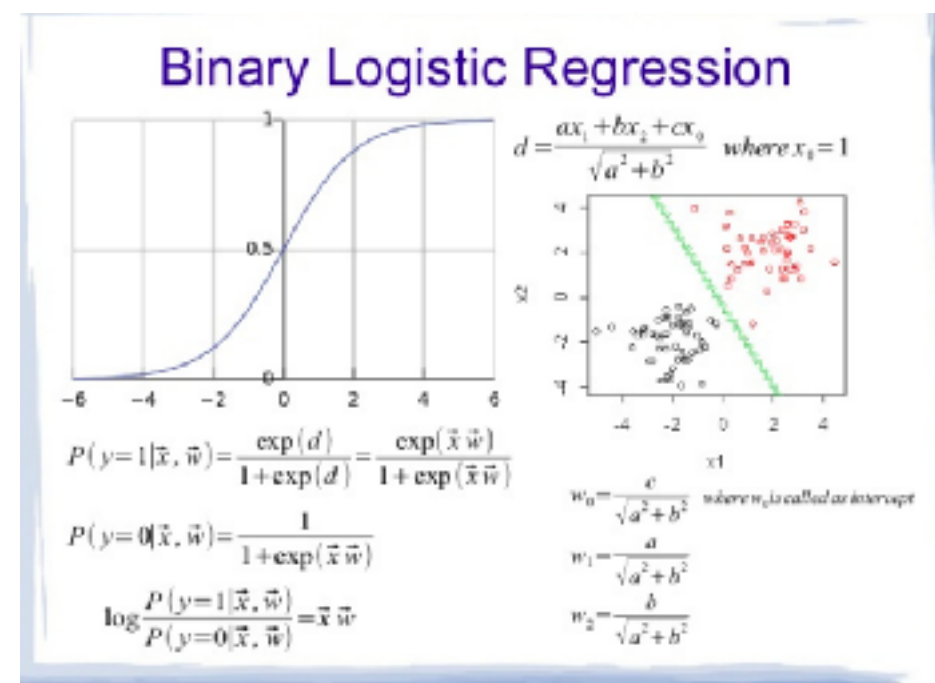
A period is assumed to be 30 days

People with the same # of rides  
could end up having different LTVs

Driver	1674103b16c39ab5 6a76884b7c2ca83c	30eedffe19d8ec6c53 841f0d46c8ab51	5ceff5a3983505de6d 021403c69750779	6ff443616dd01da84 2095c0939394baf
Tenure (in month)	27	23	33	3
rides	348	348	348	348
Avg Ride Distance	6560	5968	8265	4592
Avg Ride Duration	834	767	794	794
Prime Ratio	1.5%	2.6%	1.7%	2.1%
Lifetime Value (LTV)	\$641K	\$738K	\$743K	\$485K

# Decision Tree vs. Logistic Regression

Decision Tree and Logistic Regression can serve as the basis of LTV (predict the driver churn in the next 30 days)

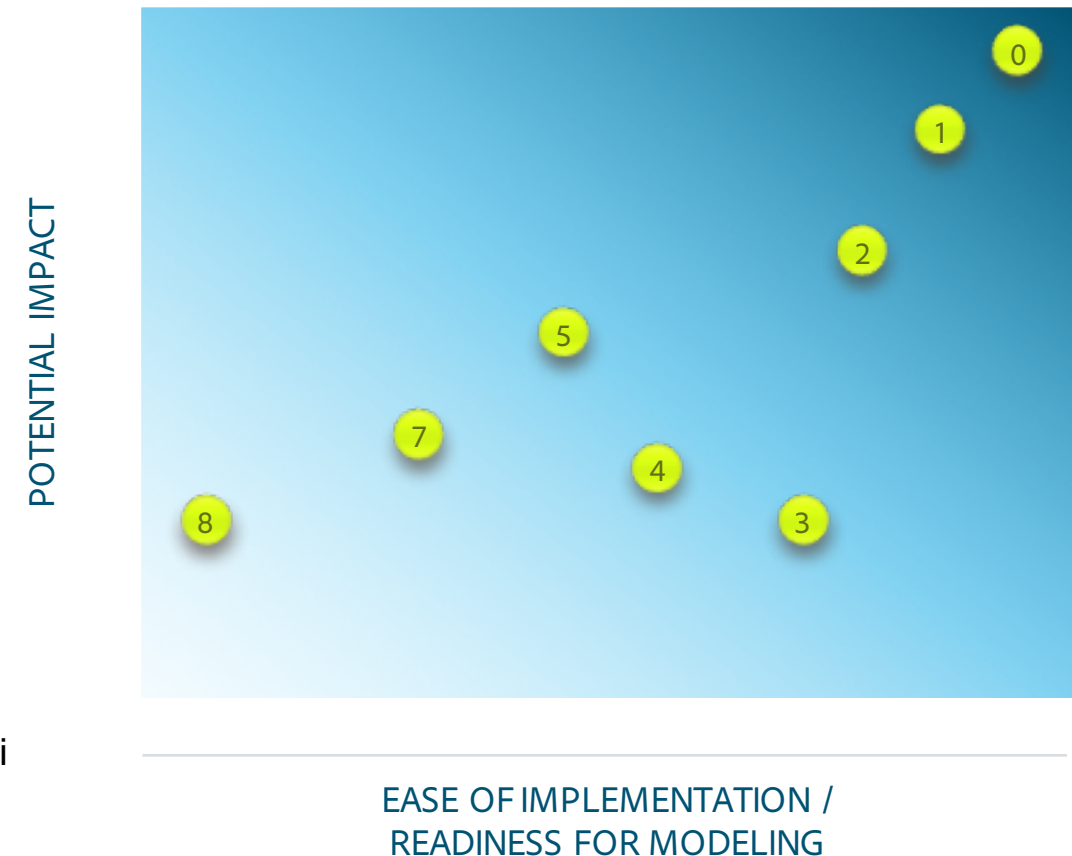


# Logistic Regression Prediction

```
getCLV<-function(r,f,m,n,cost,periods,dr,pModel){
  df<-data.frame(period=c(0),r=c(r),f=c(f),n=c(n),value=c(0))

  for(i in 1:periods){
    backstep<-df[df$period==i-1,]
    nrow<-nrow(backstep)
    for(j in 1:nrow){
      r<-backstep[j,]$r
      f<-backstep[j,]$f
      n<-backstep[j,]$n
      p<-
predict(pModel,data.frame(Recency=r,Frequency=f),type='response')[1]
      Retains<-n*p
      df<-rbind(df,c(i,0,f+1,Retains,Retains*(m-cost) / (1+dr)^i))
      df<-rbind(df,c(i,r+1,f,n-Retains,(n-Retains)*(-cost) / (1+dr)^i))
    })
  }

  return(sum(df$value))
}
```



**## caculating the CLV for a driver with R=0 days,F=10,cash flow=100,WACC/discount rate=5% for 3 periods**

**v<-getCLV(0,10,100,1,0,3,5%,model)**

<https://github.com/hq211486/Lyft/blob/master/R%20script%20retention%20model>



## Next Steps:

- Explore into more indicator variables (in addition to RFM) in the model to predict retention
- Cross-validations
- Drivers analysis: profile segmentation