Practical Guide to Calculating Customer Lifetime Value (CLV)

gormanalysis.com/practical-guide-to-calculating-customer-lifetime-value-clv/

Ben April 19, 2016

Customer Lifetime Value (CLV) is an estimation of the entire net profit attributed to a single customer. It's an important metric to understand because it helps businesses determine how much is too much to spend on advertising to acquire a single customer.

Estimating CLV can be tricky, and there's really no standard way of doing it. What follows is a technique I use that is both practical and effective.

Data Exploration

For this example we'll calculate CLV from a dataset of roughly 4,200 transactions.

TransactionID	TransactionDate	CustomerID	Amount
1	2012-09-04	1	20.96
2	2012-05-15	2	10.87
3	2014-05-23	2	2.21
4	2014-10-24	2	10.48
5	2012-10-13	2	3.94
6	2013-01-23	2	12.37
4176	2012-09-18	1000	9.69
4177	2013-06-23	1000	3.86
4178	2011-08-07	1000	4
4179	2012-10-07	1000	18.37
4180	2014-01-09	1000	3.65
4181	2011-04-30	1000	5.18

As with any analysis, the first thing we'll do is look at some basic summary statistics.

Transactions	Customers	MinTransactionDate	MaxTransactionDate	Amount
4181	1000	2010-01-04	2015-12-31	33729.91

Note that the data consists of 1000 customers who made transactions between 2010 and 2015.

TransactionsPerCustomer	AmountPerTransaction	AmountPerCustomer
4.181	8.07	33.73

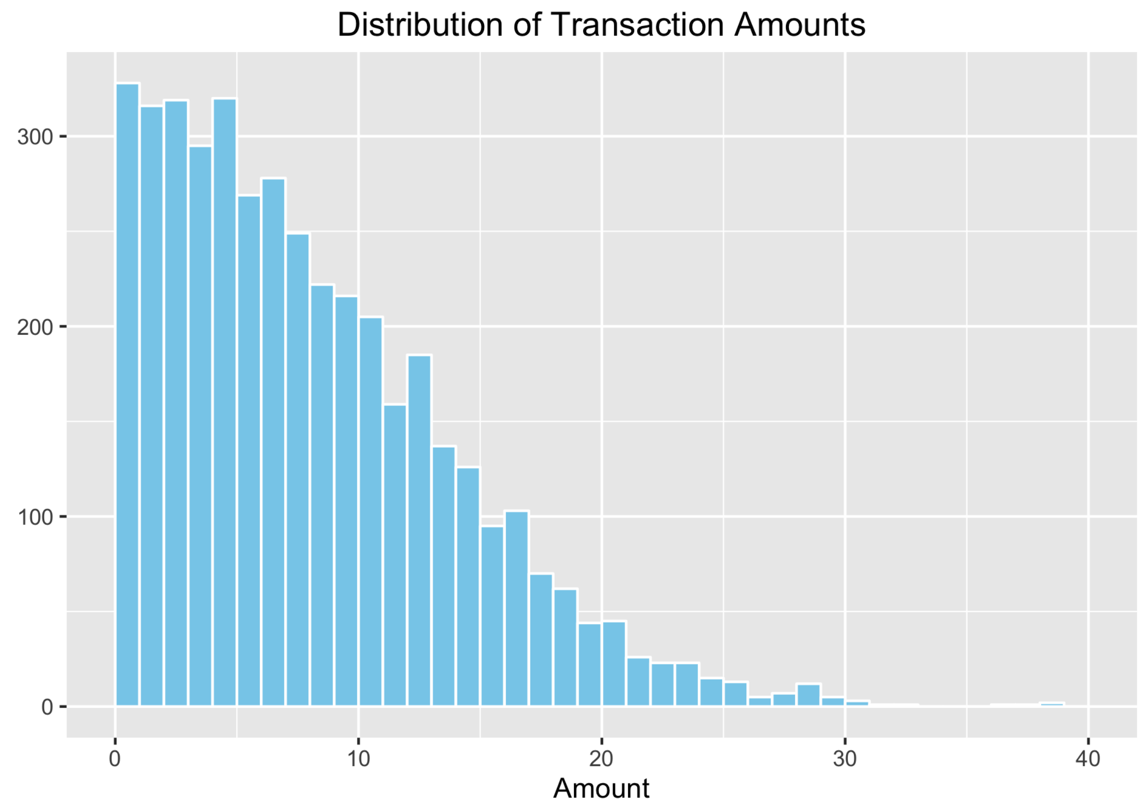
Furthermore, each customer made about 4 transactions for 8 bucks a piece, totaling close to $34. This amount can be considered a lower bound on CLV since it's the total amount spent by each customer, but we still expect existing customers to make future purchases.

Before continuing, we need to consider outlier transactions and possible data errors. For example, suppose a single transaction has Amount = $15,0000. If this is a data error, we should remove the transaction from the data entirely. If it's a legitimate but rare transaction (a baseball signed by Babe Ruth perhaps?), we need to decide how probable it is that such a transaction will occur again in the future. Depending on the likelihood of another monster purchase, we should either keep the transaction, cap it at some lower value like $5,000, or remove the transaction entirely.

Here we inspect the largest transactions

TransactionID	TransactionDate	CustomerID	Amount
2758	2013-08-31	691	38.35
261	2012-06-21	69	38.29
53	2015-01-29	13	37.27
2488	2011-07-13	632	36.94
2271	2013-04-13	573	32.81
2642	2011-05-16	663	31.4
583	2013-03-16	145	30.43
416	2013-12-31	100	30.31
3961	2013-07-28	957	30.01
1342	2013-06-28	345	29.99

We *could* use a statistical test to check for outliers, but here it's pretty clear that none exist. Plotting the entire distribution of transaction amounts should give us more confidence in our assertion.



Measuring Historic CLV

Now we need to consider the biggest source of error in our $34 CLV lower bound – some of the underlying customers are brand new and others have been customers for almost five years. Obviously the newer customers will have (generally) spent less on average than the old ones. So, we need to separate the customers into groups based on how long ago they were acquired (e.g. customers acquired in 2010, vs customers acquired in 2011, …). Fortunately, there's a free app for that.

Since we have 5 years worth of data, let's use Trinalysis to separate customers into annual origin periods starting on 2010-01-01, and measure their purchases annually. (Note: Using annual periods will remove any effects/biases of seasonality purchasing.)

Now let's take a look at some of the important triangles for our analysis.

ActiveCustomers

Origin	12	24	36	48	60	72
2010-01-01 – 2010-12-31	172	93	104	91	103	82
2011-01-01 – 2011-12-31	170	92	98	89	88	
2012-01-01 – 2012-12-31	163	109	98	90		
2013-01-01 – 2013-12-31	180	103	102			
2014-01-01 – 2014-12-31	155	90				
2015-01-01 – 2015-12-31	160					

NewCustomers.cmltv

Origin	12	24	36	48	60	72
2010-01-01 – 2010-12-31	172	172	172	172	172	172
2011-01-01 – 2011-12-31	170	170	170	170	170	
2012-01-01 – 2012-12-31	163	163	163	163		
2013-01-01 – 2013-12-31	180	180	180			
2014-01-01 – 2014-12-31	155	155				
2015-01-01 – 2015-12-31	160					

Transactions

Origin	12	24	36	48	60	72
2010-01-01 – 2010-12-31	260	177	195	164	163	128
2011-01-01 – 2011-12-31	263	189	192	155	142	
2012-01-01 – 2012-12-31	263	195	179	155		
2013-01-01 – 2013-12-31	276	195	213			
2014-01-01 – 2014-12-31	251	185				
2015-01-01 – 2015-12-31	241					

Amount.cmltv

Origin	12	24	36	48	60	72
2010-01-01 – 2010-12-31	2255.07	3613.85	5271.87	6627.43	7922.95	8956.55
2011-01-01 – 2011-12-31	2238.46	3758.03	5465.12	6702.14	7861.77	
2012-01-01 – 2012-12-31	2182.92	3878.26	5230.43	6505.42		
2013-01-01 – 2013-12-31	2181.85	3611.81	5230.75			
2014-01-01 – 2014-12-31	1833.85	3263.05				
2015-01-01 – 2015-12-31	1912.37					

Now we can use these triangles to build other useful triangles like

CustomerRetention = ActiveCustomers/NewCustomers.cmltv

Origin	12	24	36	48	60	72
2010-01-01 – 2010-12-31	1	0.54	0.6	0.53	0.6	0.48
2011-01-01 – 2011-12-31	1	0.54	0.58	0.52	0.52	
2012-01-01 – 2012-12-31	1	0.67	0.6	0.55		
2013-01-01 – 2013-12-31	1	0.57	0.57			

Origin	12	24	36	48	60	72
2014-01-01 – 2014-12-31	1	0.58				
2015-01-01 – 2015-12-31	1					

TransactionsPerCustomer = Transactions/ActiveCustomers

Origin	12	24	36	48	60	72
2010-01-01 – 2010-12-31	1.51	1.9	1.88	1.8	1.58	1.56
2011-01-01 – 2011-12-31	1.55	2.05	1.96	1.74	1.61	
2012-01-01 – 2012-12-31	1.61	1.79	1.83	1.72		
2013-01-01 – 2013-12-31	1.53	1.89	2.09			
2014-01-01 – 2014-12-31	1.62	2.06				
2015-01-01 – 2015-12-31	1.51					

AmountPerTransaction = Amount/Transactions

Origin	12	24	36	48	60	72
2010-01-01 – 2010-12-31	8.67	7.68	8.5	8.27	7.95	8.07
2011-01-01 – 2011-12-31	8.51	8.04	8.89	7.98	8.17	
2012-01-01 – 2012-12-31	8.3	8.69	7.55	8.23		
2013-01-01 – 2013-12-31	7.91	7.33	7.6			
2014-01-01 – 2014-12-31	7.31	7.73				
2015-01-01 – 2015-12-31	7.94					

Some takeaways thus far:

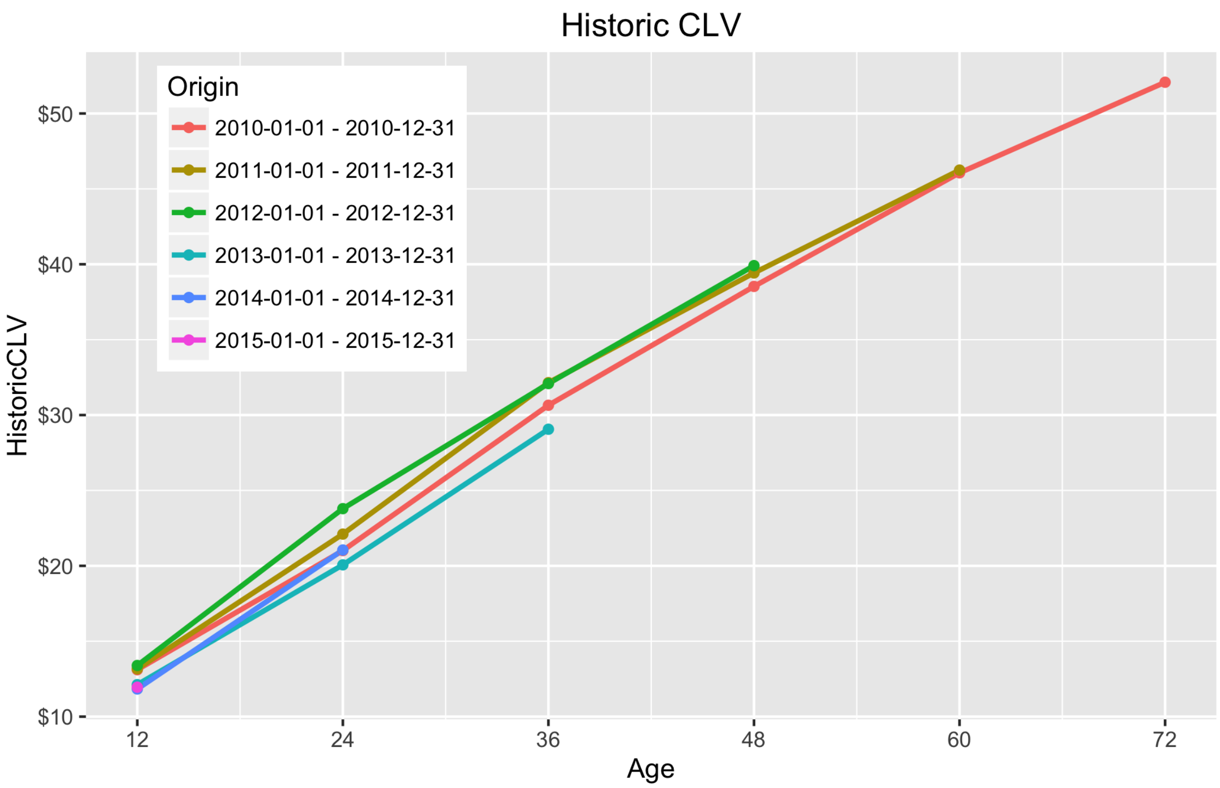
- Roughly 55% ~ 60% of customers are retained into a 2nd year, at which point retention is very strong
- 2nd+ year retained customers make more transactions on average than all 1st year customers combined
- Transaction amounts are generally flat over time across all groups

Customer retention, transaction frequency, and transaction amount are all variables that contribute to estimating an accurate CLV. However, we can encapsulate these variable by simply measuring the cumulative amount spent per customer over time. Dividing the Amount.cmltv triangle by the NewCustomers.cmltv triangle will give us annual measurements of the cumulative amount spent per customer in each group of annually acquired customers. This is also known as Historic CLV.

HistoricCLV=Amount.cmltv/NewCustomers.cmltv

Origin	12	24	36	48	60	72
2010-01-01 – 2010-12-31	13.11	21.01	30.65	38.53	46.06	52.07
2011-01-01 – 2011-12-31	13.17	22.11	32.15	39.42	46.25	
2012-01-01 – 2012-12-31	13.39	23.79	32.09	39.91		
2013-01-01 – 2013-12-31	12.12	20.07	29.06			
2014-01-01 – 2014-12-31	11.83	21.05				
2015-01-01 – 2015-12-31	11.95					

A plot of the historic CLV for each cohort looks like this

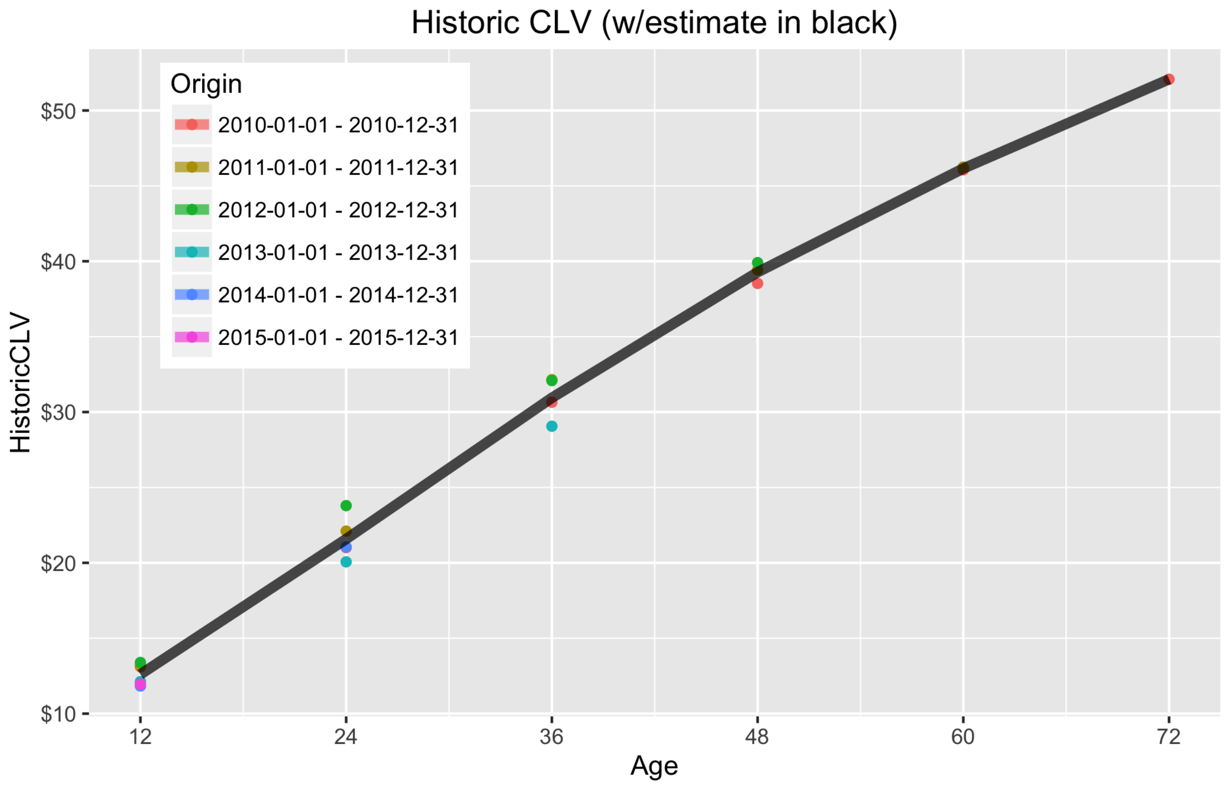


Here we can draw some nice conclusions. Firstly, customers acquired in 2010 have spent $52.07 to date. Secondly, each group of customers appears to exhibit a very similar pattern of spending. This should give us confidence in assuming $52.07 is a decent lower bound on CLV.

At this point, we'd like to combine all of our data to create a single curve of Historic CLV. A simple, but effective approach to doing this is to take a volume weighted average of the Historic CLV for each group at each Age, weighted by the number of customers in each group. In this example, we'd get

Age	HistoricCLV
12	12.6
24	21.58
36	30.95
48	39.28

Age	HistoricCLV
60	46.15
72	52.07



(Note: *Age* represents the time elapsed since the *start* of each customer group. So, when a customer group is 12 months old, the average customer in that group is actually 6 months old.)

Extrapolation

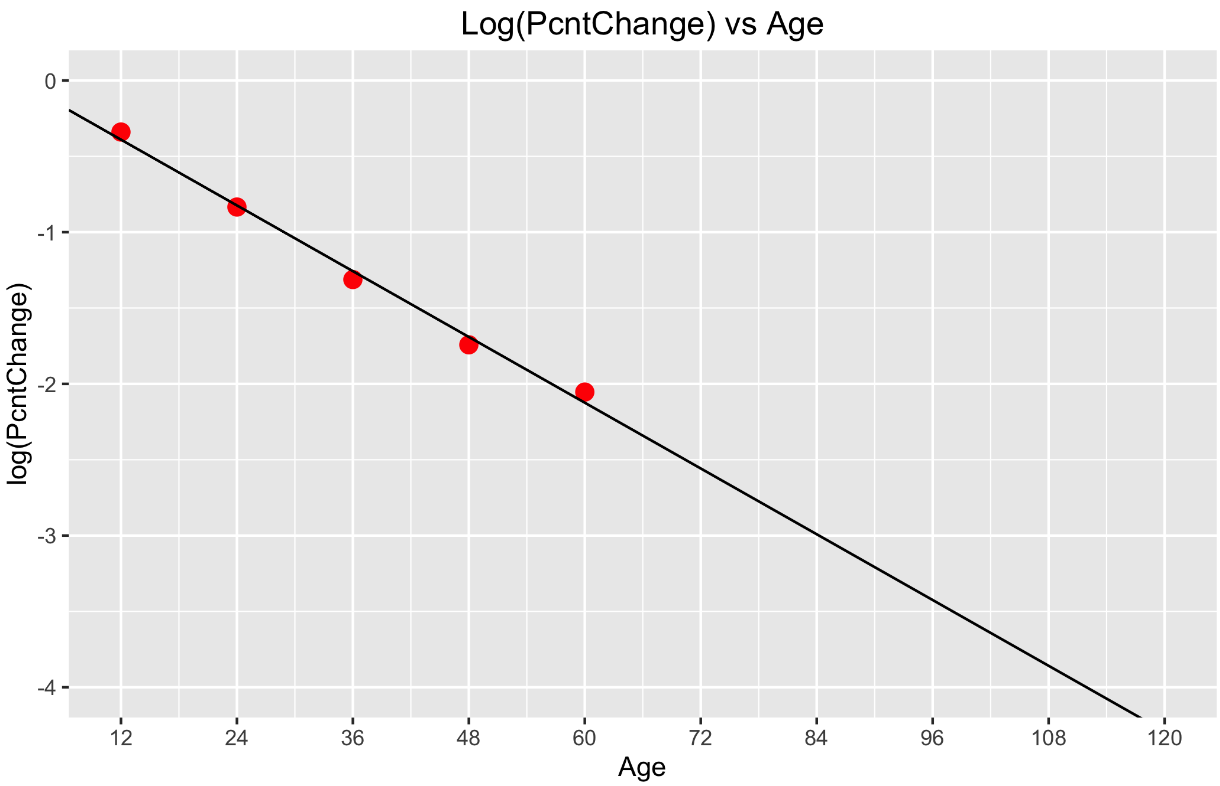
Perhaps the hardest part of estimating CLV is extrapolating the Historic CLV to account for the entire relationship of a customer with your business. This is particularly difficult because businesses change over time, so using a purely mathematical model is rarely the best approach. Nonetheless, here’s one way we can extrapolate our Historic CLV curve to account for the entire future relationship with a customer.

First, calculate the percent change in HistoricCLV from Age_i to Age_i+1.

Age	HistoricCLV	PcntChange
12	12.6	0.71
24	21.58	0.43
36	30.95	0.27
48	39.28	0.18
60	46.15	0.13

Age	HistoricCLV	PcntChange
72	52.07	

Next, observe that the PcntChange has a log-linear relationship with Age. That is, the **log of the percent change in Historic CLV from year to year is linearly correlated with Age**. This means we can use linear regression to extrapolate log(PcntChange) based on Age.



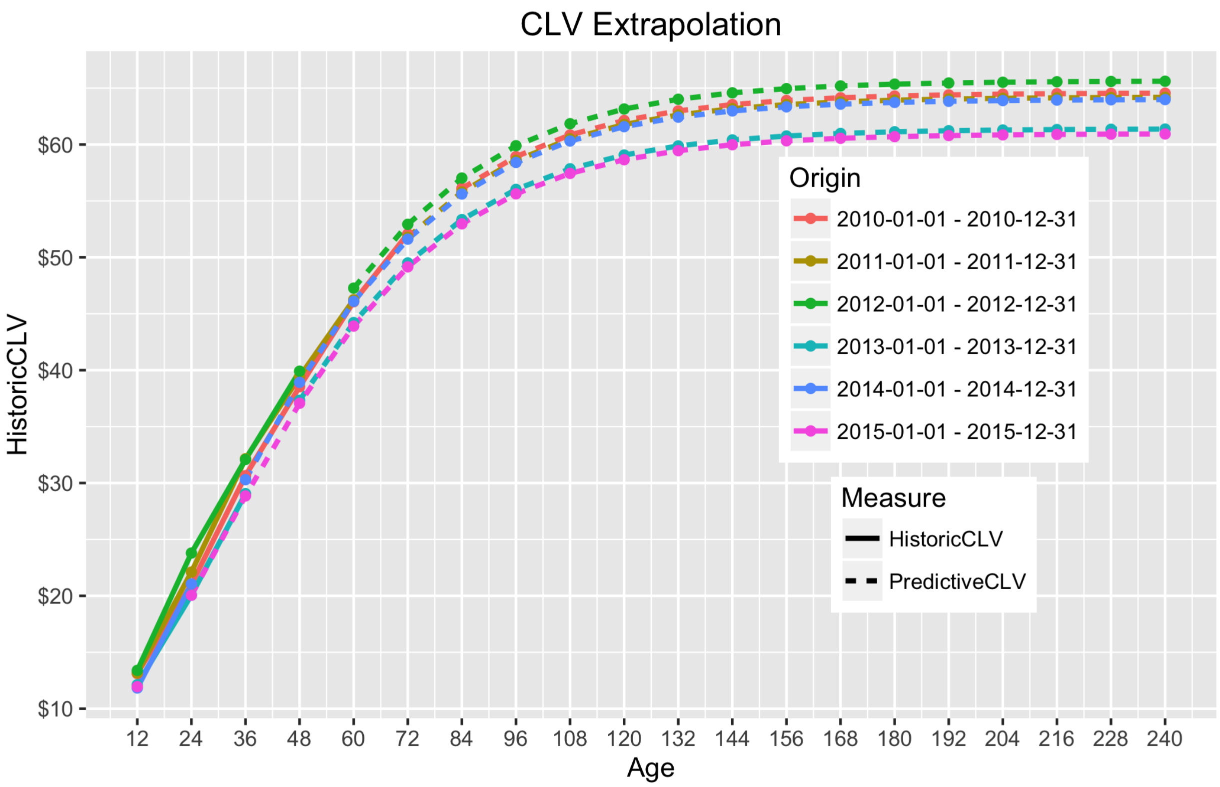
In this case we find that log(PcntChange) = 0.0443 – 0.0361 * Age which means PcntChange = exp(0.0443 – 0.0361 * Age). With this model, we can build the following table.

Age	ModelLogPcntChange	ModelPcntChange	CLVFactor
12	-0.39	0.68	5.1
24	-0.82	0.44	3.04
36	-1.26	0.28	2.11
48	-1.69	0.18	1.64
60	-2.12	0.12	1.39
72	-2.56	0.08	1.24
180	-6.46	0	1
192	-6.89	0	1
204	-7.33	0	1
216	-7.76	0	1
228	-8.19	0	1

Age	ModelLogPcntChange	ModelPcntChange	CLVFactor
240	-8.63	0	1

Now we can extrapolate the Historic CLV to any future point in time. The CLV estimate should converge as age goes to infinity, but for the sake of practicality it's often best to extrapolate CLV to year 20 or 30 depending on the nature of your business.

Here's a look at our previously calculated Historic CLV estimates extrapolated out to year 20.



If we extrapolate our global model (which combines information from every period), we find that CLV = 1.39 * $52.07 ≈ $72.

Going Further

There are a few last things to be aware of regarding this methodology…

1. It does not take into account expenses. So, our CLV estimate isn't actually measuring customer *value* as much as it's measuring customer *spend* or *revenue.* However, you can deduct expenses from the HistoricCLV triangle to get a more accurate estimate of CLV if you'd like.
2. We didn't take inflation into account. (Again this is not hard to do, if you have accurate annual inflation estimates.)
3. We didn't segment our customers into different qualitative groups which could distort our estimate. For example, it might make sense to estimate CLV for men and women separately depending on the nature of the business.