

How do you value your customers



Vince Pan

<https://github.com/constiny/LTV>



A question from Liquor Store Manager



*Who should I send the special gift to?
Type your answer in Slack.*

Jessie



Total

\$ 400

Ellie



\$ 400



What is the Customer Lifetime Value?

By definition, customer lifetime value is the present value of the future (net) cash flows associated with the customer.

In plain English, **how much will the customer buy in the future?**



Why do we care?

- Determine customer acquisition spend
- Assist on evaluating marketing campaign ROI
- Help marketing budget allocation
- Some use for sales prediction sanity check



Data

Raw data:

300K transaction log data



Aggregation Data:

3K Customers Behavior

CustomerID	OrderID	Timestamp	Amount
a	001	2012-01-04	45.00



CustomerID	# of Orders	First Order Date	Last Order Date	Amount	Target Amount
a	5	2012-01-04	2012-08-24	205.00	35.00

Y2010

Dec

Jan

Feb

Mar

Apr

May

Jun

Jul

Aug

Sep

Oct

Nov

Y2011

Predictor

Target

Predictor - Train (80%)

Target 80% Train

Predictor - Test (20%)

Target 20% Test

Base model



Present

Jessie

\$ 110

170

120

?

$$\$400/10 * 2 \text{ months} = \$80$$

Ellie

\$ 50

50

70

60

90

80

?

$$\$400/10 * 2 \text{ months} = \$80$$

Dec

Jan

Feb

Mar

Apr

May

Jun

Jul

Aug

Sep

Oct

Nov



Decomposition

Total Sales = Number of transactions * Single transaction amount

For single customer

= Number of transaction in Unit time

~ Poisson Distribution

* Customer Purchasing Lifetime Length

~ Exponential Distribution

* Single Transaction Amount

- Gamma Distribution

For all customers

Total Sales = Customer1 Sales + ... + CustomerN Sales

- Gamma Distribution



Maximum Likelihood Estimation

LifeTimeValue model

a.k.a. Pareto/NBD - Gamma Gamma model

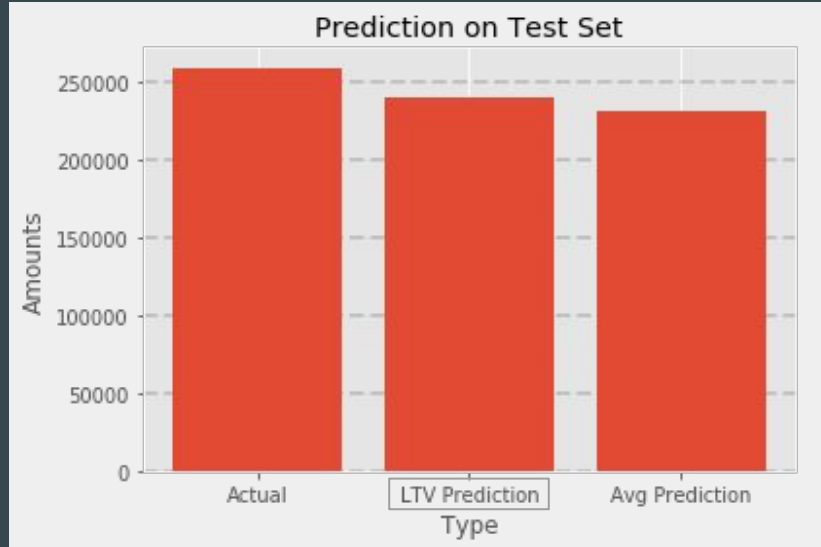
Model Comparison on Validation Set

Method	Base	LTV	Supervised Learning	
Algorithm	Lifetime monthly avg	Pareto/NBD	Random Forest	Linear Regression
RMSE*	3140	1660	1808	1774

$$RMSE = \sqrt{\frac{\sum (\hat{y}_i - y_i)^2}{n}}$$



Final Model Prediction



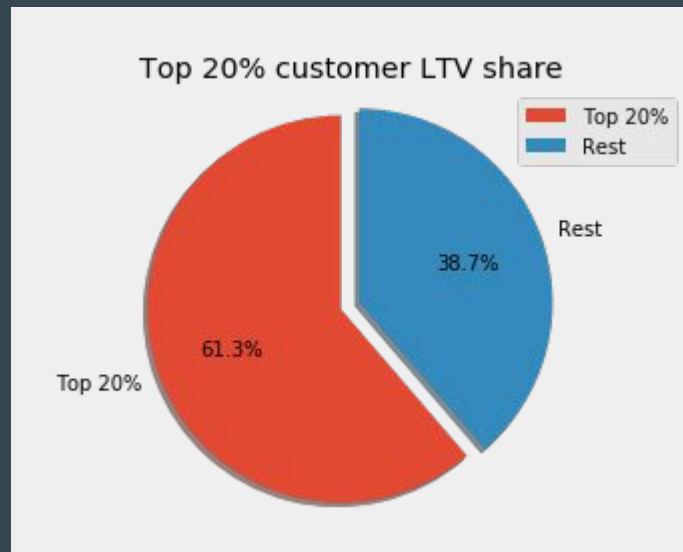
Prediction on	# of Purchase	\$ of Single Purchase	LTV
Jessie	0.43	179	78
Ellie	0.97	74	72



80/20 rules?

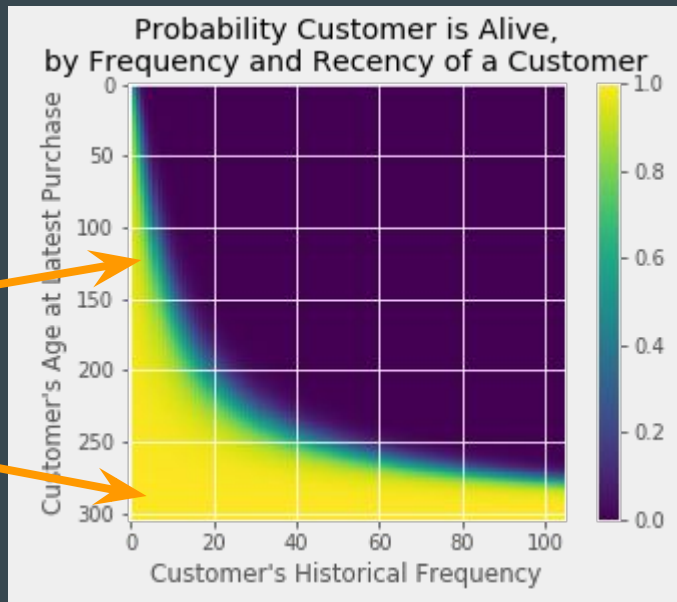
Curious about who should be your VIP?

Sort by the LTV and prioritize your resource on the top.



Churn Warning

Prediction on	# of Purchase in next 2 month	Probability to be alive/active at present
Jessie	0.43	0.88
Ellie	0.97	0.99



Takeaways

1. LTV model reduce bias in customer spending prediction than using the mean.
2. LTV helps identify the most value customer
3. Alternative way to predict churn



What's next

1. Integrate with Churn Prediction. Would it be a good way to fill in the cost-benefit matrix?
2. Expend the model to include more transactional information, i.e. what they buy.



Question?



The squeaky wheel gets the grease.



Prediction on	# of Purchase	Probability to be alive/active at present	\$ of Single Purchase	LTV
Jessie	0.43	0.88	179	78
Ellie	0.97	0.99	74	72



Appendix



Model Comparison on Validation Set

Method	Base		LTV	
Algorithm	Lifetime monthly avg	Pareto/NBD	BetaGeoBeta Binom	BetaGeo
RMSE*	3140	1660	3177	2106

$$RMSE = \sqrt{\frac{\sum (\hat{y}_i - y_i)^2}{n}}$$



Other Model Comparison on Validation Set

Method	Base	LTV	Supervised Learning		
Algorithm	Lifetime monthly avg	Pareto/NBD	Random Forest	Support Vector Machine	Linear Regression
RMSE*	3140	1660	1808		1774

$$RMSE = \sqrt{\frac{\sum (\hat{y}_i - y_i)^2}{n}}$$



Why do we care?

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The five assumptions of Pareto/NBD model

- i. While active, the number of transactions made by a customer in a time period of length t is distributed Poisson with transaction rate λ .
- ii. Heterogeneity in transaction rates across customers follows a gamma distribution with shape parameter r and scale parameter α .
- iii. Each customer has an unobserved “lifetime” of length τ . This point at which the customer becomes inactive is distributed exponential with dropout rate μ .
- iv. Heterogeneity in dropout rates across customers follows a gamma distribution with shape parameter s and scale parameter β .
- v. The transaction rate λ and the dropout rate μ vary independently across customers.

The three assumptions of Gamma-Gamma model

- The monetary value (e.g., \$, £, e) of a customer's given transaction varies randomly around their average transaction value.
- Average transaction values vary across customers but do not vary over time for any given individual.
- The distribution of average transaction values across customers is independent of the transaction process.

Model Comparison on Validation Set

Method	Base			LTV	
Algorithm	Lifetime monthly avg	Last 2 months	Pareto/NBD	BetaGeoBeta Binom	BetaGeo
RMSE*	3140	3129	1660	3177	2106

$$RMSE = \sqrt{\frac{\sum (\hat{y}_i - y_i)^2}{n}}$$

