

ICO Price Optimization

Cox Automotive Case Study



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Problem Overview

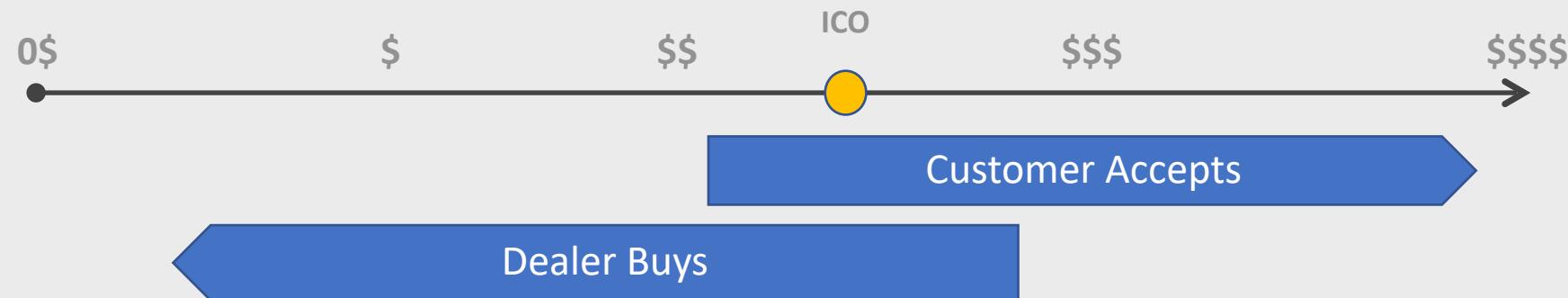
1. Instant Cash Offer (ICO) - Prediction

2. Instant Cash Offer (ICO) - Optimization

Customer vs. Dealer

ICO = Instant Cash Offer

If a customer accepts the ICO, then Dealers have the chance to buy the vehicle at ICO.



Predicting Dealer Buys

ICO = Instant Cash Offer

Historical data has ICO values paid by the dealer to the consumer.



Goal: Build a model to predict ICO values based on historical dealer buys.

Historical Dataset includes: Make, model, mileage, vehicle condition etc.....

ICO Prediction Steps

Dataset

	Variables	ICO Value
1			
2			
3			
.			
.			
40491			

Training Data (80%)

Testing Data (20%)

1. Split dataset for model training and testing
2. Add & remove variables
3. Fit several models on training data
4. Report errors on testing data*

Mean Absolute Error = | Actual ICO - Predicted ICO |

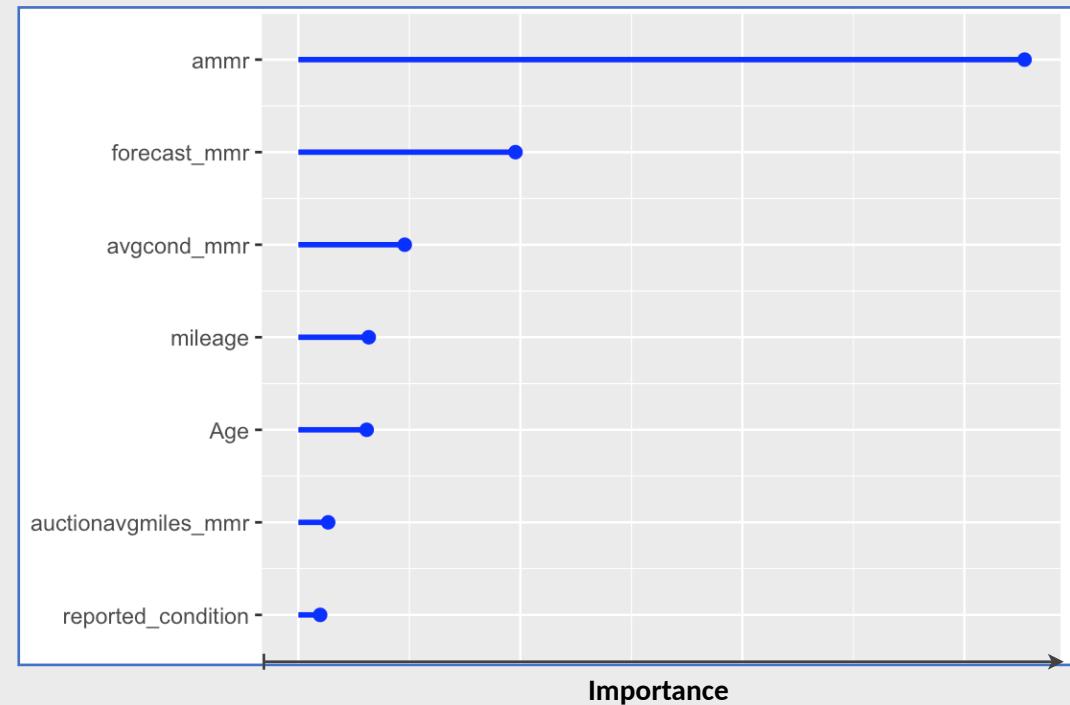
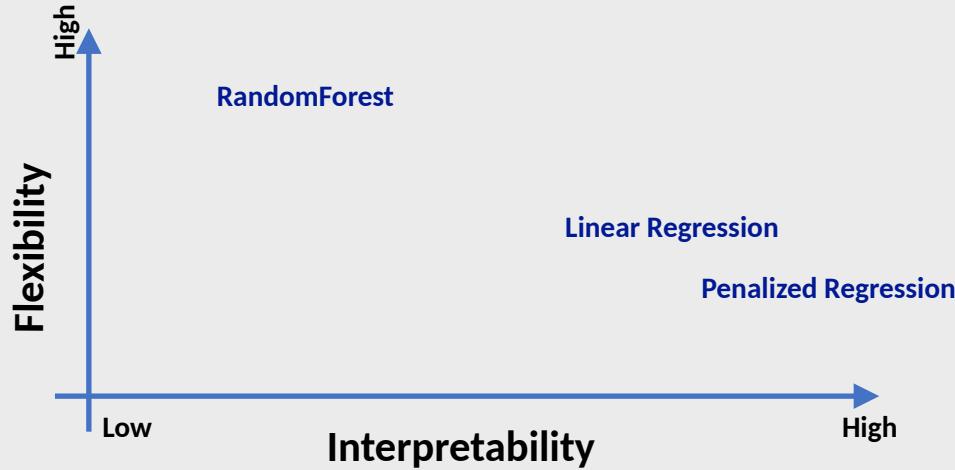
Mean Square Error = (Actual ICO - Predicted ICO)^2

*Why? Report on test to simulate how our model will preform on unseen future data.

ICO Models & Insights

Key Variables Identified

Models Considered



Ammr = Whole price estimate from Manheim Market Report

Forecast_mmr = Whole price forecast 5 weeks future

Avgcond_mmr = Average condition for vehicle type

Mileage = Odometer mileage

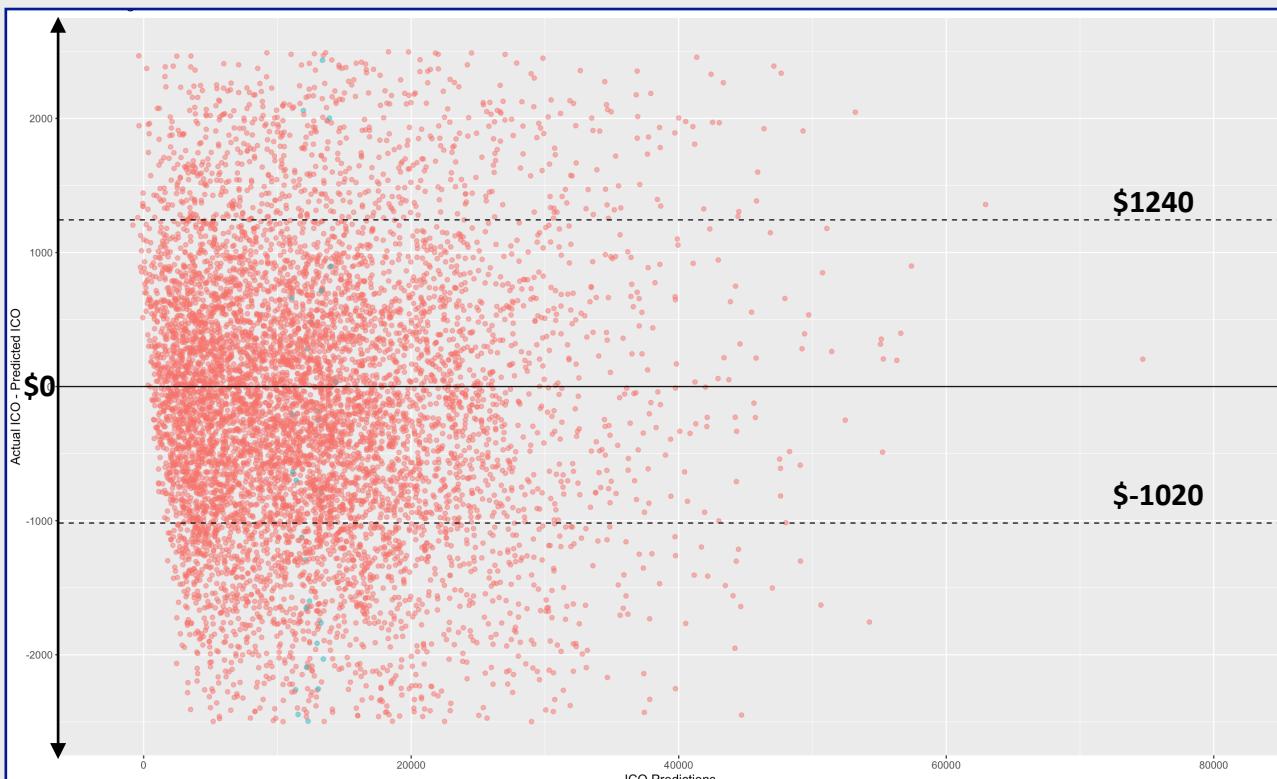
Age = Offer Date - Model Year (created variable)

Random Forest Model beats Linear model:

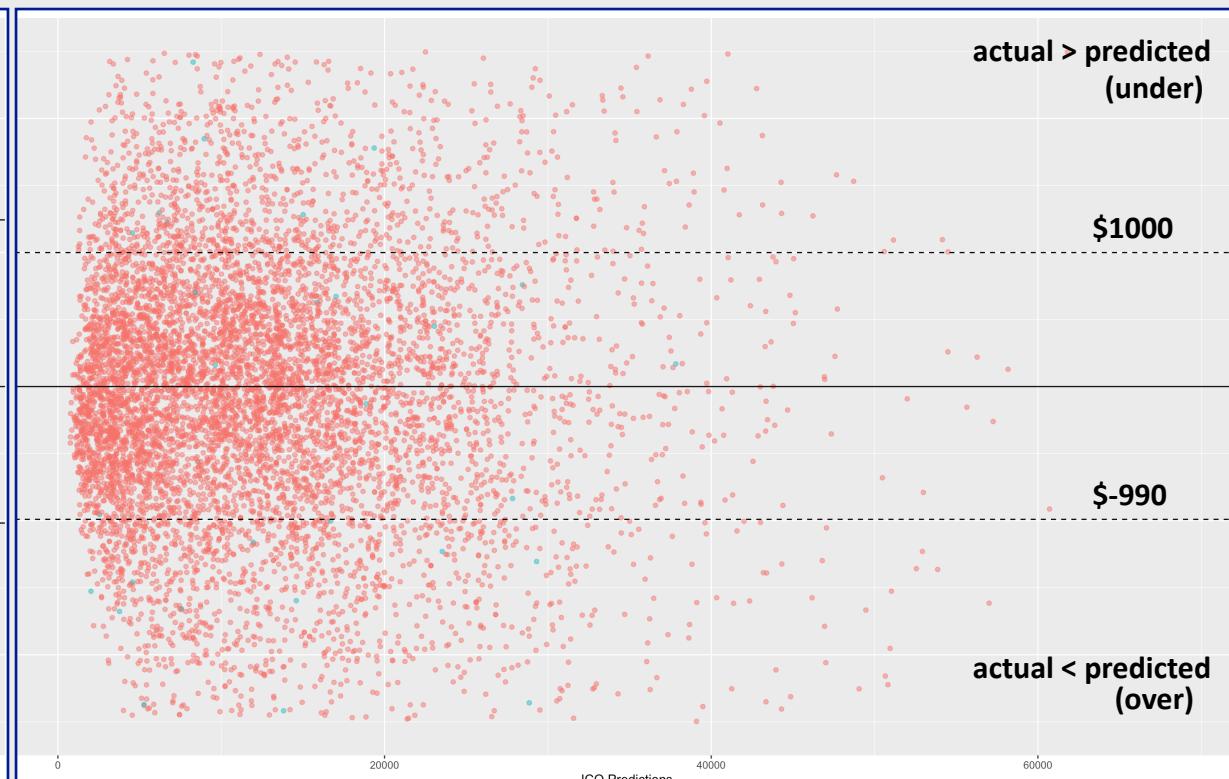
X-Axis = Predicted ICO
Y-Axis = Actual ICO - Predicted ICO

1. Overall smaller ICO errors -> business impact **more accurate predictions reduces COX risk.**
2. Symmetrical errors -> **under predicting less** than Linear model means **more consumer accepts.**

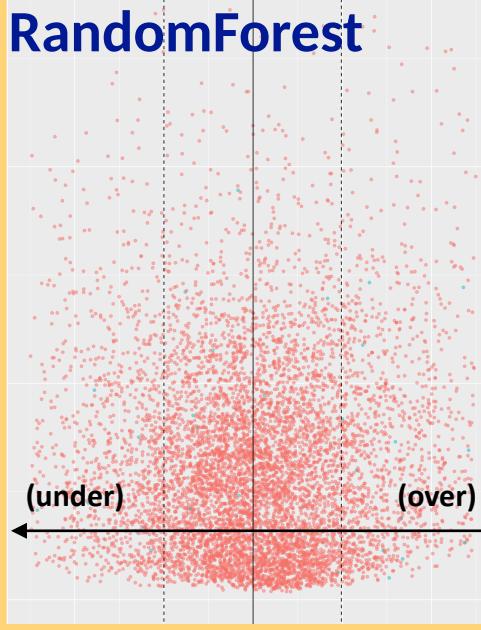
Linear Regression



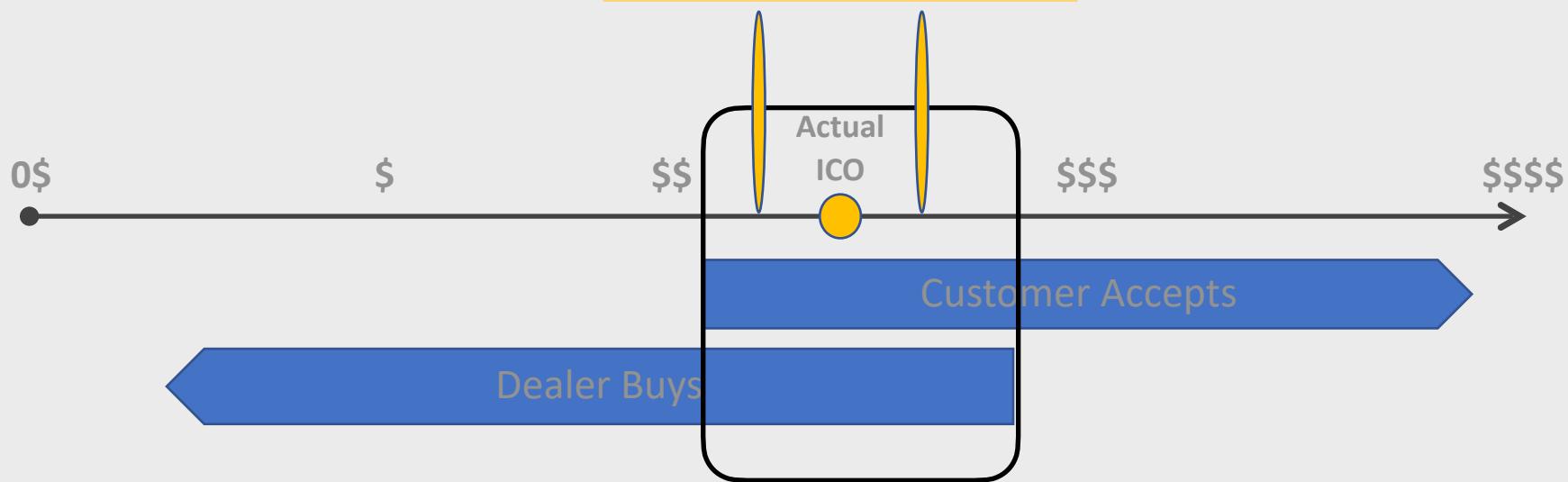
RandomForest



Predicting Dealer Buys



ICO = Instant Cash Offer



Goal: Build a model to predict ICO values based on historical dealer buys.

Problem Overview

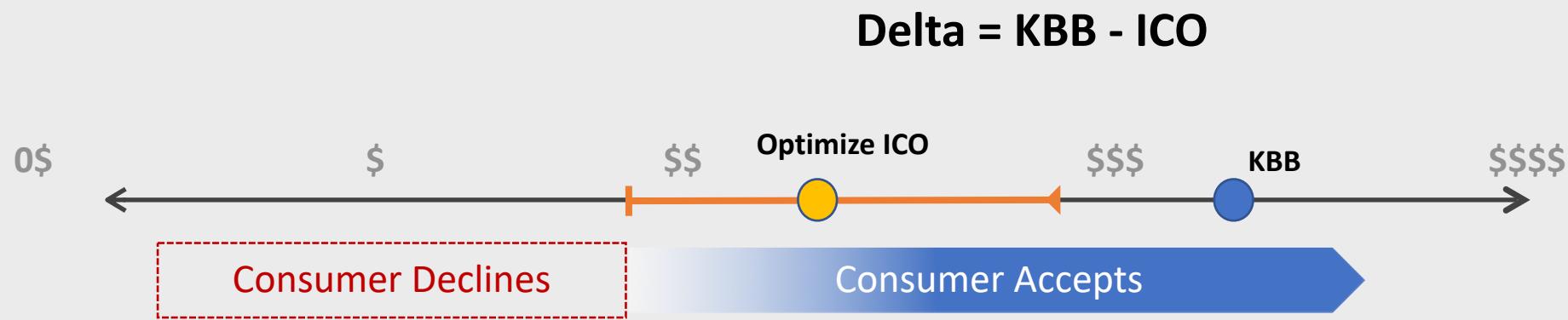
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2. Instant Cash Offer (ICO) - Optimization

Part 2: Optimizing ICO

KBB = Kelly Blue Book

The market value of selling the car.



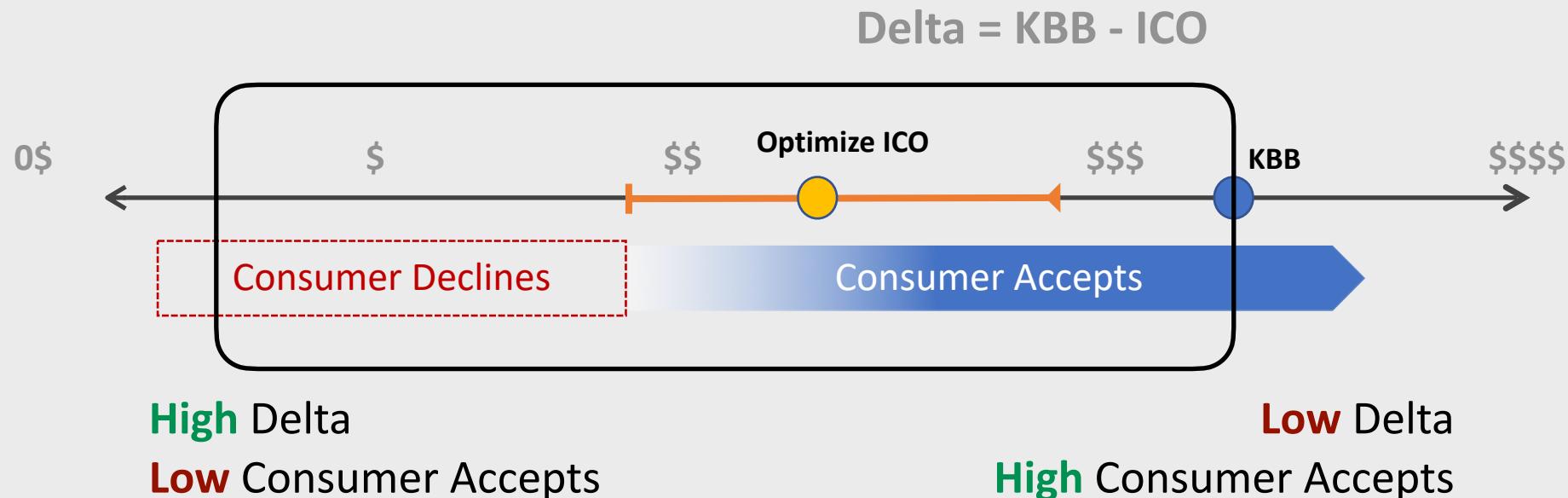
Part 2: Optimizing Dealer Profit

KBB = Kelly Blue Book

Formally:

Profit = Probability (accept | delta) * delta

Profit = Probability Consumer Accepts * Delta



Available Data

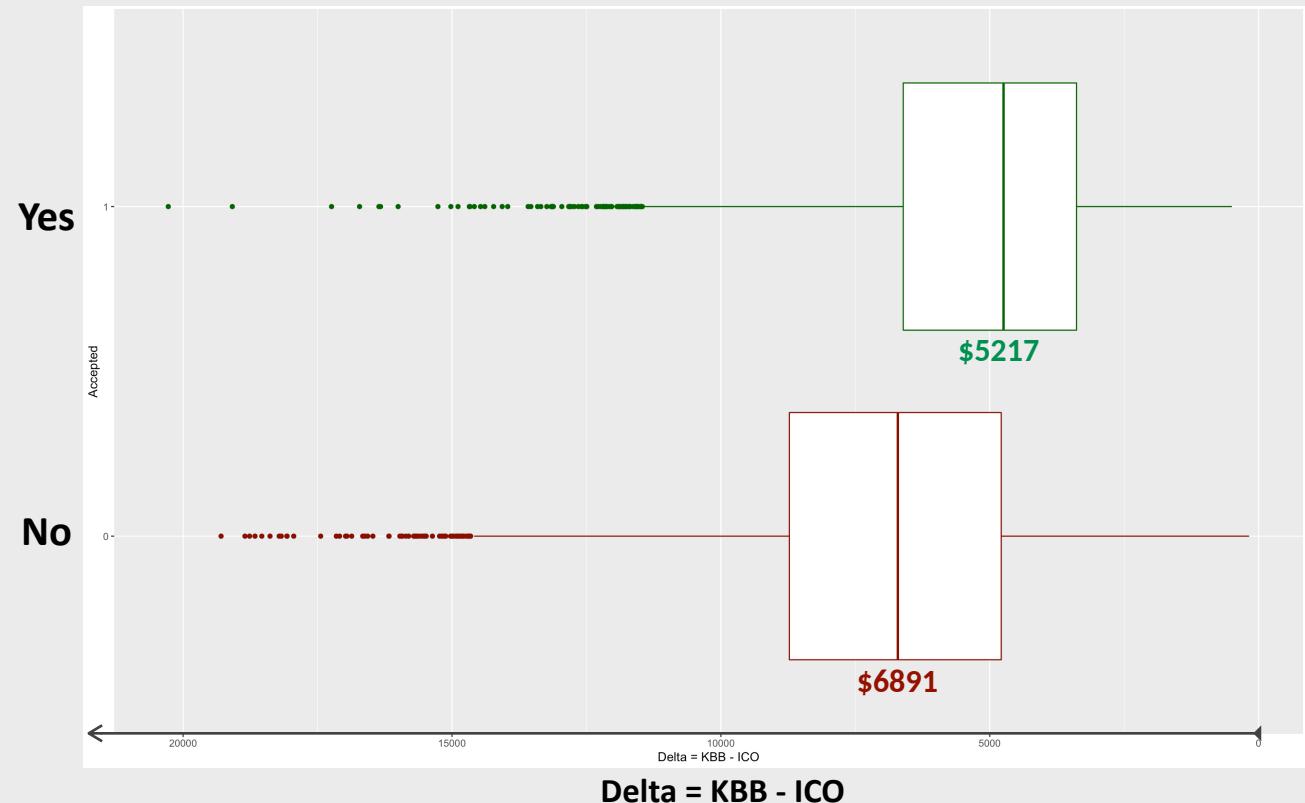
Dataset

	KBB	ICO	Accept
1	\$	\$	Yes
2	\$	\$	No
3	\$	\$	Yes
.	.	.	.
.	.	.	.
15243	\$	\$	Yes

> KBB - Market value of the car

> ICO - Offer made to Consumer

> Accept - Consumer accepted or not



> Consumers accepted ICO offers on avg* **\$5217** less than KBB

> Consumers did not accept ICO offers on avg* **\$6891** less than KBB

Modeling Expected Profit

Expected Profit = Probability Consumer Accepts * Delta

Linear:

Delta = \$6491

31% Chance of Accept

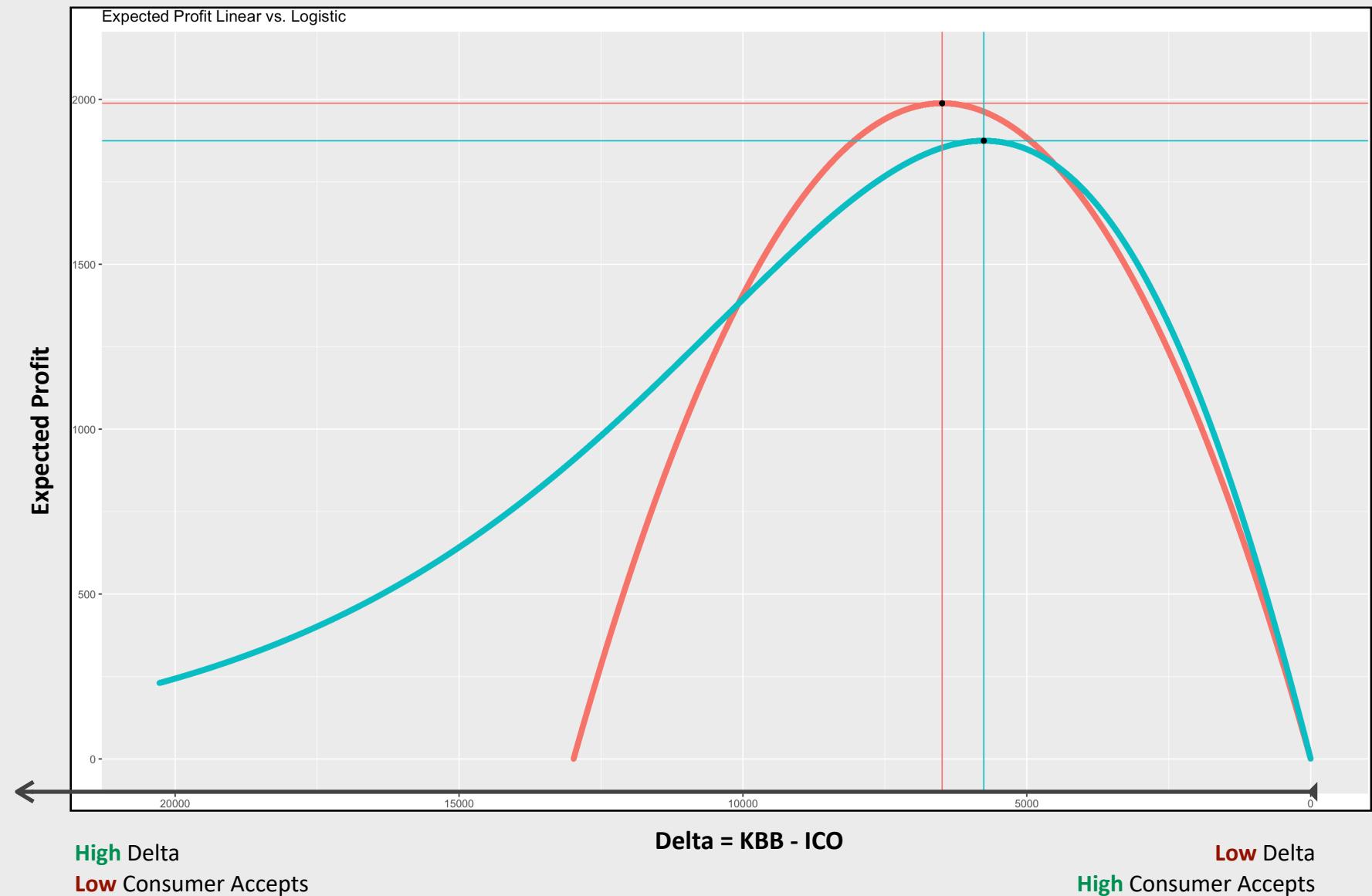
Expected Profit =
\$1988.13

Logistic:

Delta = \$5758

33% Chance of Accept

Expected Profit =
\$1874.4



Why Logistic over Linear?

Linear:

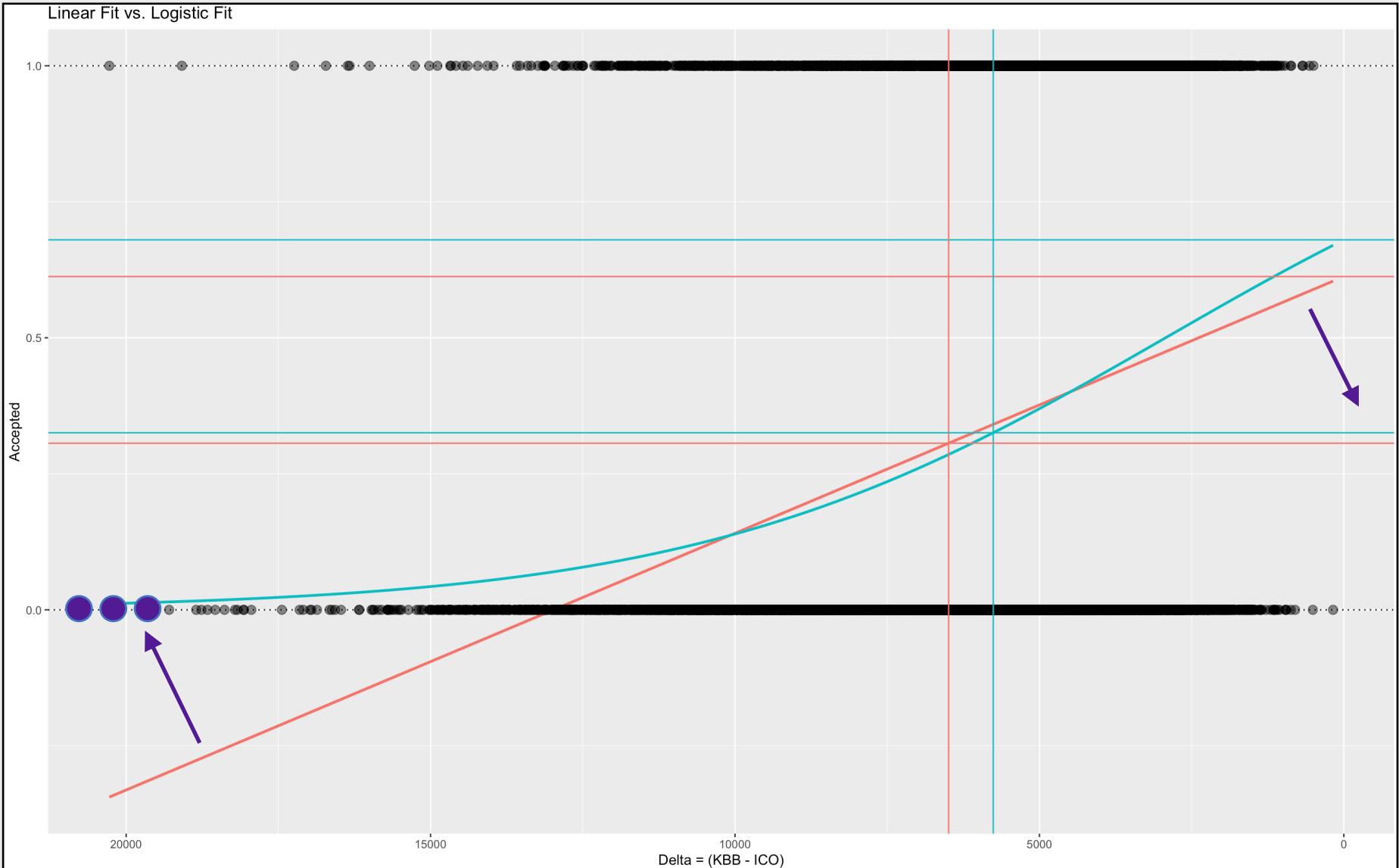
Delta = \$6491

31% Chance of Accept

Logistic:

Delta = \$5758

33% Chance of Accept



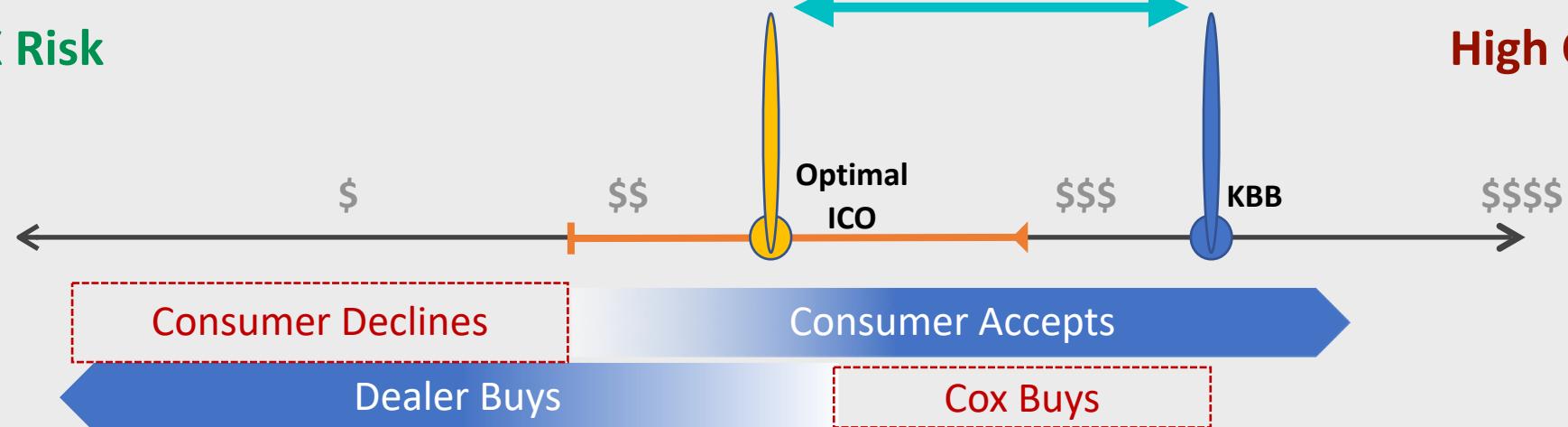
Part 2: Optimizing Dealer Profit & Minimizing Cox Risk

KBB = Kelly Blue Book
Delta = KBB - ICO

Dealer Profit
&
Low COX Risk

Logistic Model:
Optimal Delta = \$5758

Customer Cash
&
High COX Risk



Summary

1. RandomForest **predicts ICO dealer buys** with error of ~ \$1000 over/under.
2. Logistic Regression shows **ICO predictions should be optimized** to \$5758 less than KBB value to maximize dealer profit & reduce Cox risk.

3. Next Steps

Questions

Back Up

Confidence in Logistic

1. Sample data w/ replacement
2. Fit logistic model on sample
3. Extract coefficients
4. Plug into profit function derivative to get Delta value that maximizes profit.
5. Repeat 1000x

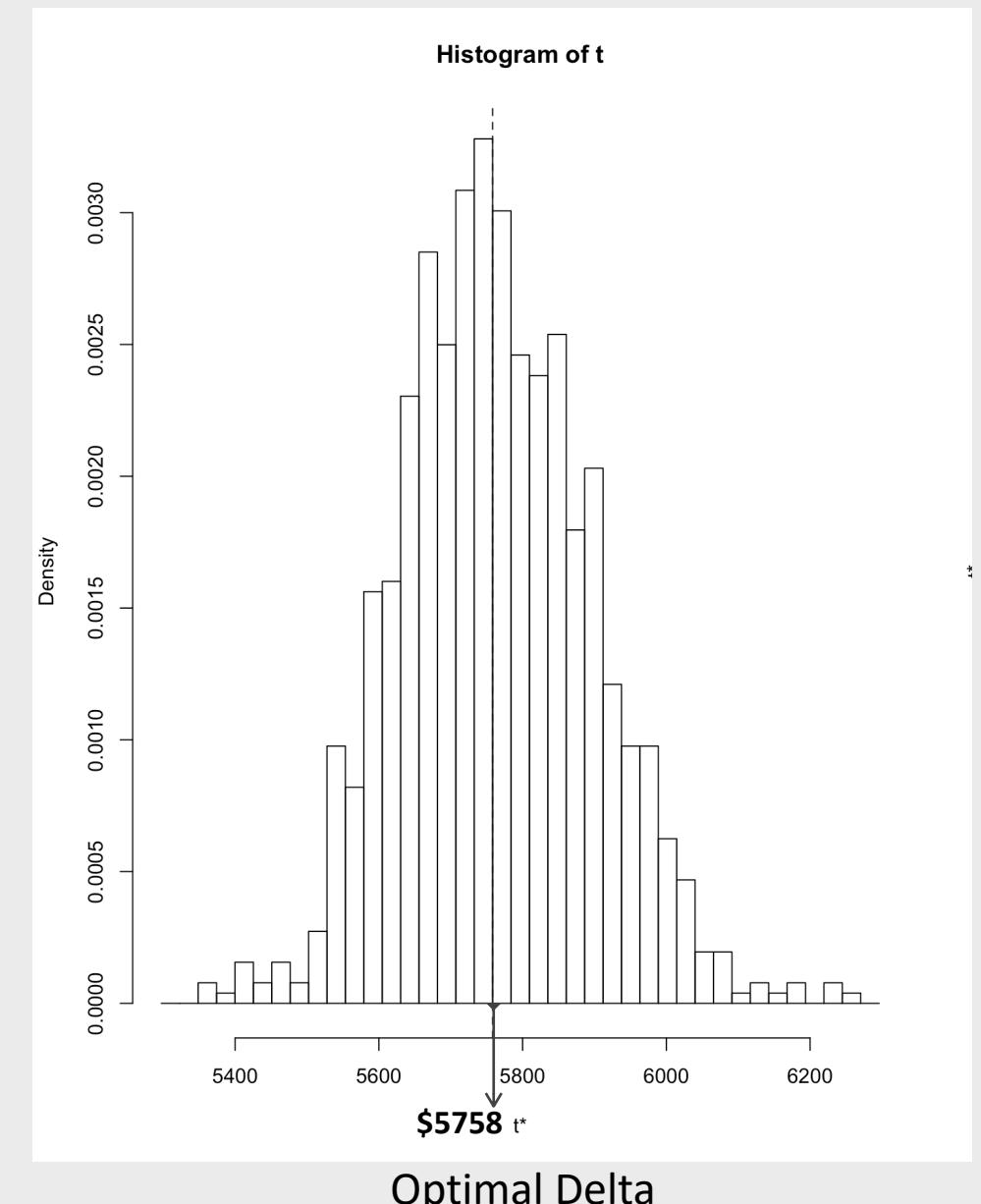
$$P(\text{accept} | d) = 1 / (1 + e^{-(a * d + b)})$$

$$\text{Profit} = P(\text{accept} | d) * d$$

$$\frac{\partial}{\partial d} \left(\frac{d}{1 + e^{-(ad+b)}} \right) = \frac{e^{ad+b} (e^{ad+b} + ad + 1)}{(e^{ad+b} + 1)^2} = 0$$

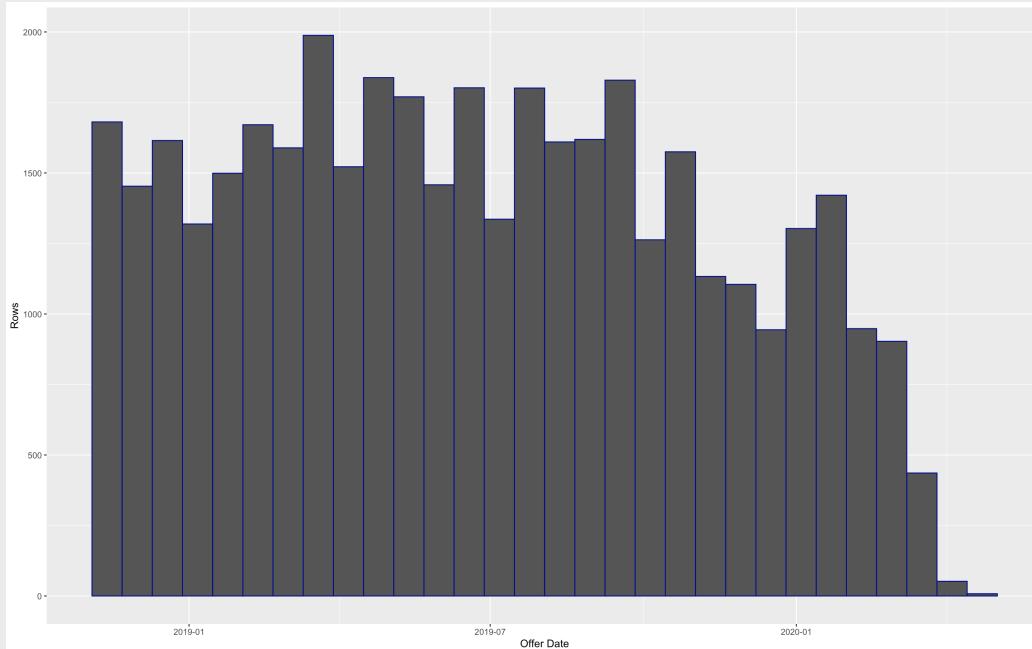
$$d = \frac{-W(e^{b-1}) - 1}{a} \approx \frac{-W(2.71828^{b-1}) - 1}{a}$$

Logistic:



Prediction Data

Number of rows over time



Nov 2018

April 2020

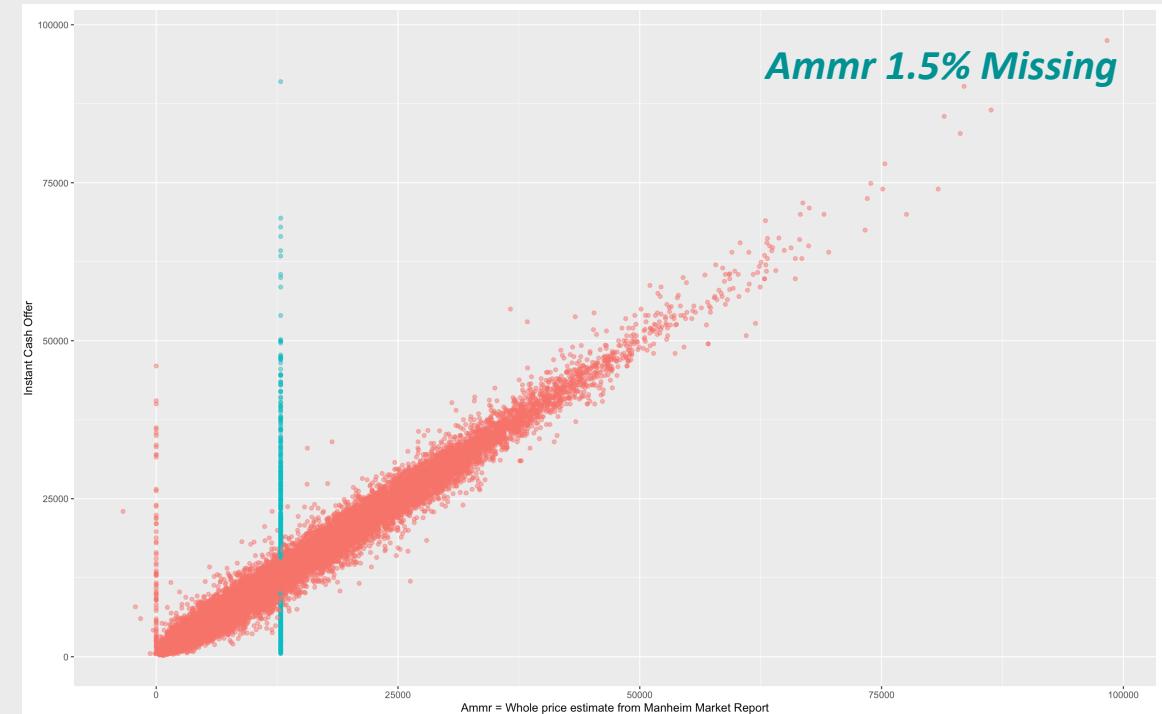
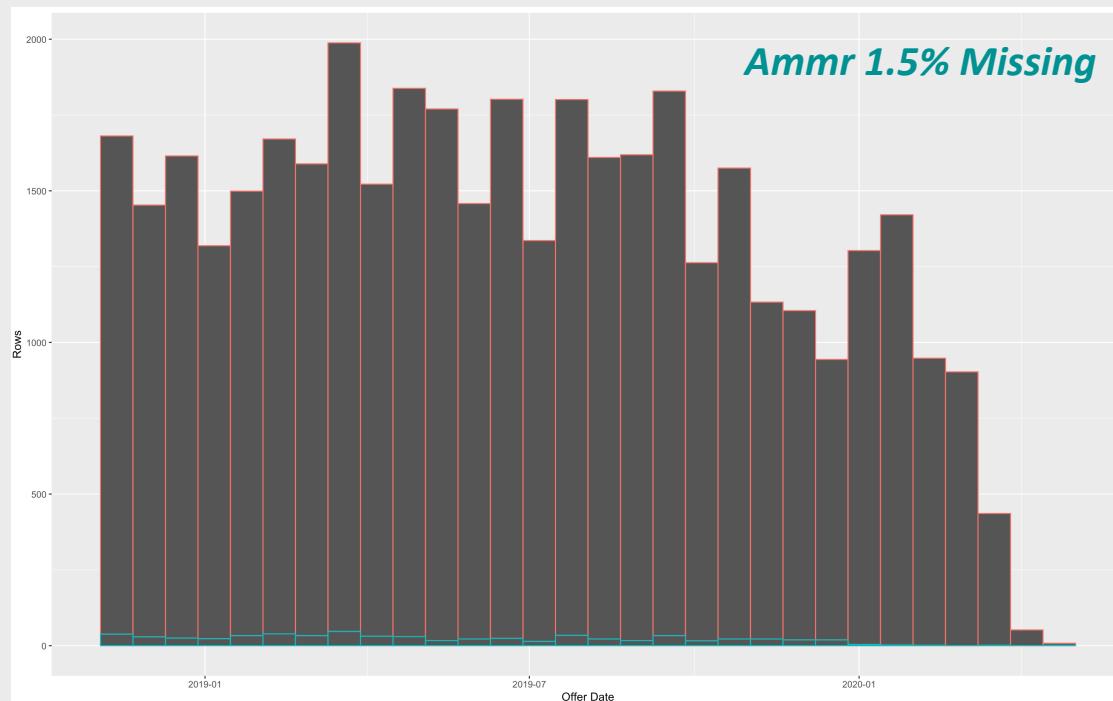
Trade in Value

`quantile(df$trade_in_value)`

0% 25% 50% 75% 100%
200 5900 11300 17700 97500

Prediction Data

Missing Values of strongest predictor Ammr



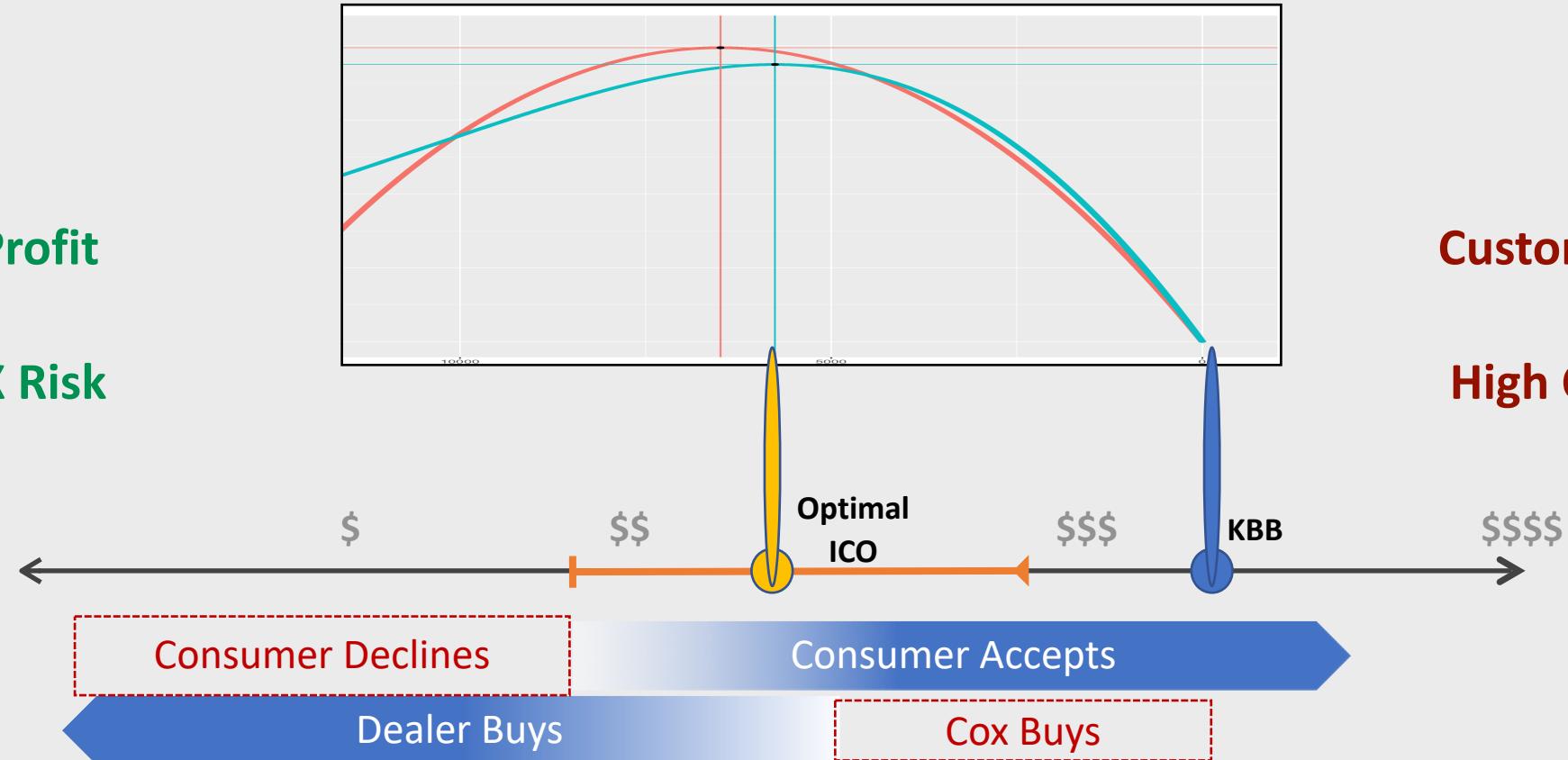
KBB = Kelly Blue Book

Part 2: Optimizing Dealer Profit & Minimizing Cox Risk

The market value of selling the car.

**Dealer Profit
&
Low COX Risk**

**Customer Cash
&
High COX Risk**



X-Axis = Predicted ICO
Y-Axis = Actual ICO - Predicted ICO

Model Errors - Explainability vs. Accuracy

Linear Regression

Average magnitude of errors is \$1100

Linear tends to make worse underestimate errors compared to the RandomForest

RandomForest

Average magnitude of errors is \$990

(-) when predicted > actual
(+) when predicted < actual



MAE = \$1100

$$\text{sqrt}(\text{MSE}) = \text{sqrt}(\$4,807,894) = \$2190$$

MAE = \$990

$$\text{sqrt}(\text{MSE}) = \text{sqrt}(\$2,821,194) = \$1680$$

Customer Perspective

ICO = Instant Cash Offer

The price Cox predicts a customer's vehicle is worth.

