FICO

Generating predictive models for loan default rate with Action Effect

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Agenda

- What is FICO® Decision Optimizer?
- FICO® Action Effect Modeling Methodology
- Loan Default Rate Prediction
- Conclusions

FICO, Decision Optimizer and the Decision Apps

What is FICO® Decision Optimizer?

- FICO® Decision Optimizer (DO) is a **Decision App**. It combines easy to use data processing and **analytic model artefact** tooling which automates the generation of **simulation** or **optimization** of business decisions.
  - reads input data from CSV or SQL database, automatically extracting data schema and columns statistics
  - allows users to create high level mathematical expressions
  - offers common analytic model file artefact processing
  - determines how to convert the business actions into variables that can be optimized or simulated.
- Empowers **business analyst** with a tool than can be used to **automatically create assignment problems** that can process commonly used analytic model artefacts.

FICO® Decision Optimization: From Data to Deployment

Data

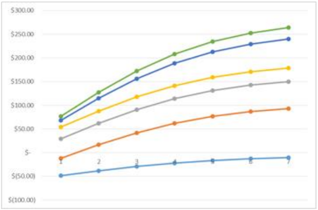
Action-Effect Modelling

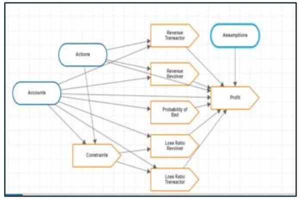
Mathematical Optimization

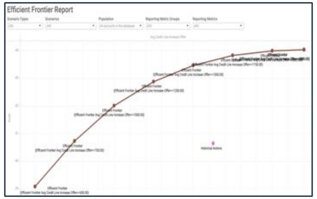
Strategy Selection

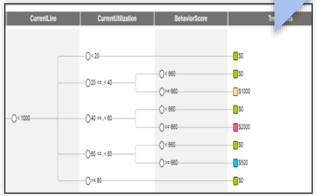
Deployment

var1	var2	var3	var4
2	963.28	12395.42	15000
2	51.03	1679.45	12000
2	798.90	10177.84	10000
2	25.79	414.45	13500
2	49.66	188.52	11000
2	312.39	6721.70	7000
4	329.55	4049.40	6500
2	56.26	527.57	11500









Continuous Learning & Improvement

What is an Action Effect Model?

Action Effect Models predict how different segments react to the action, e.g. loan take up rate by customer price:

- Low Score, High response
- High Score, Low response

Scope:

- **Estimate Target** score in response to Action values, and the inference of Predictors.
- **Incorporating business knowledge/assumption on expected/modeled behavior**

Input: **Historical data** containing, for several accounts, the Action applied to that account, the resulting Target and several other characteristics some of which will be elected as Predictors.

Output: - **Scores** used to predict the target value for an account given a new Action value.
- **Modeling** the Target score in response to Action.

Action-Effect Model Requirements

What Properties Should an A-E Model Have?

- Control for historical targeting bias:
  - Historically, different actions are taken on different segments e.g. risky customers are offered a high price
  - Need to predict an outcome for all possible actions, not just those actions taken historically
- Should be intuitive:
  - Response should be directionally correct w.r.t. action, e.g. higher TU at lower price
  - Predictions should rank order across customer segments, e.g. higher TU for riskier customers
- Should be predictive:
  - Capture differences across customer segments & 'validate well' Out-of-Time (OOT),
  - Include 'Intercept' or 'Base Model' terms
- Should be sensitive:
  - Dependent on the action you take, e.g. loan price, amount
  - Includes 'Interaction' or 'Cross-Effect' terms

What is an Action Effect Model?

- Base Model
  - Re-weighting to control for targeting bias
  - No variation with action
  - Objective: Minimisation of segment-level error between Actual and Predicted target (weighted LSE)
  - Decision variables : Base Target scores for each predictor and bin
  - Model type: Quadratically constrained, convex
- Action Effect Model
  - Final weighted LSE model includes the effect of the action
  - Fitted using model assumptions around curve shape and expected response to action (base score)
  - Outcome: Given user-defined shape coefficients α, and decision variables $Intercept$ and $Range$, AE scores are:

$$s(rec, var, a) = Intercept(var, a) + Range(var, a)\alpha(rec, var, a)$$

for each record rec, predictor var and action a.

AE scores are combined with Base for the **final scores**

Modelling options:

- Cross-bin linear constraints on Intercepts and Ranges can be user-defined
- Target scores can be restricted (to limit noise)

Loan Default Rate Case Study –AE Models OOT Validation

Loan Default Rate Prediction with AE

- For every account in the portfolio we want to predict probability of loan default (bad rate) given the segment the account belongs to given characteristics and the offer (loan amount).
- Bad rate:
  - $P(x|(j,p))$
    - x -> probability bad ($\{0,1\}$), determines the outcome (rate)
    - j -> segment, defined by account characteristic
    - p -> action

    - The action p is the amont offered to the customer
    - Segments j are defined as low/medium/high risk
    - Bad rate x will be associated with a loss in loan amount optimization

Model Performance Summary

- Development records for model training. Out-of-Time (OOT) sample for validation and generalization.
- The performance window for the OOT sample overlaps with the COVID period, unlike the development data.

WalkIn Segment		
	Development	OOT Overall
Total # Observations	31,602	53,860
Bad Rate	3.20%	4.50%
FICO Model Gini	44.60%	39.0%
Bank Model Gini		50.8%

- Volume of applications in OOT sample is higher compared to the development sample
- Portfolio-level bad rate has increased in the OOT sample, greater increase observed across applications sourced from the Cross-Sell segment
- Model Performance: Drop in model performance (Gini) compared to Dev, higher Gini observed for Bank model in OOT.

Stability Analysis – WalkIn

- Population Stability Index PSI Analysis – Population distribution is stable in OOT, for all in-model characteristics and action. However, shift in the population towards higher action bins

Loan Amount	Development (%)	Development Bad Rate	OOT (%)	OOT Bad Rate (Actual)
<= 125000	12.8%	3.0%	9.0%	2.3%
<= 250000	18.8%	2.6%	14.8%	2.8%
<= 450000	28.5%	2.8%	24.8%	3.3%
<= 1000000	27.6%	3.3%	31.2%	4.2%
<= 10000000	12.3%	4.7%	20.2%	8.4%

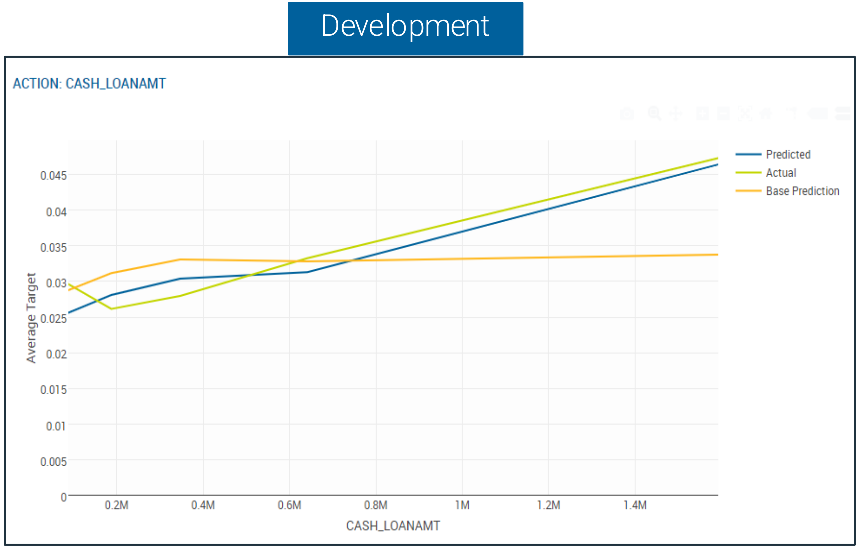
- Higher action bins are characterised with higher bad rates. With increased population falling in this bin, the bad rate increase is significant (4.7% in Dev to 8.4% in OOT).
- The increase in bad rate translates to an increase in exposure at risk, with ~20% of applications being approved higher balance.

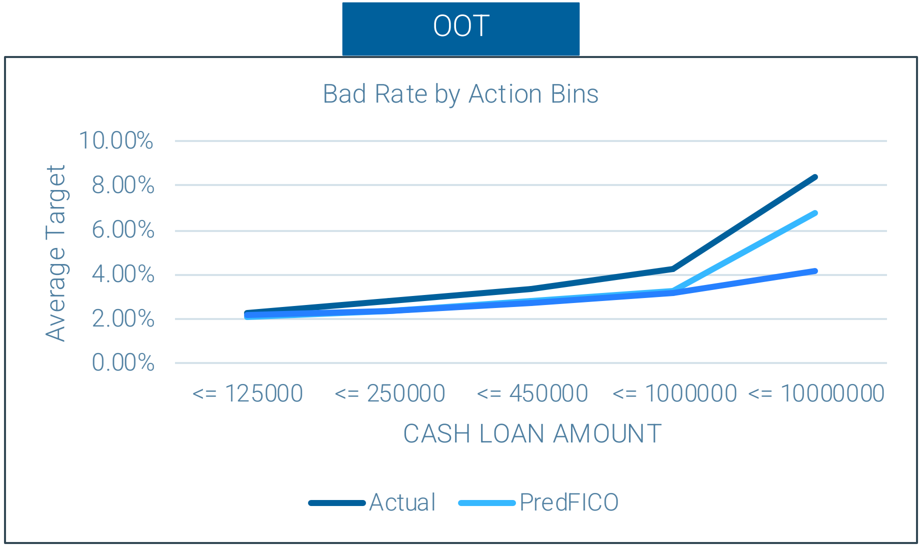
Profile Analysis – Development vs. OOT - WalkIn

Development				OOT			
Action Bins	Avg VERIFIED_INCOME	Avg EQU_Score	Avg DTI_IN	Action Bins	Avg VERIFIED_INCOME	Avg EQU_Score	Avg DTI_IN
<= 125000	39157	777	0.16	<= 125000	29177.36	788	0.20
<= 250000	35893	765	0.24	<= 250000	37877.27	774	0.31
<= 450000	46938	751	0.33	<= 450000	42843.92	755	0.44
<= 1000000	67804	746	0.45	<= 1000000	129321.15	744	0.60
<= 10000000	**124461**	**743**	**0.62**	**<= 10000000**	**111339.94**	**732**	**0.83**

- Historically, high loan amounts have been extended to riskier population (low bureau scores and high Day-To-Income (DTI)), with high affordability (high income)
- In OOT, a similar lending pattern is observed but the risk appetite of the bank has increased. Similar loan amounts are being extended to a riskier population, primarily at higher loan amount bins:
  - Average bureau score reduced from 743 in development to 732 in OOT
  - Population in OOT characterised with lower income and very high DTI (increased from 62% in dev to 83 % in OOT at high loan amounts) compared to development

Actual vs. Predicted - WalkIn

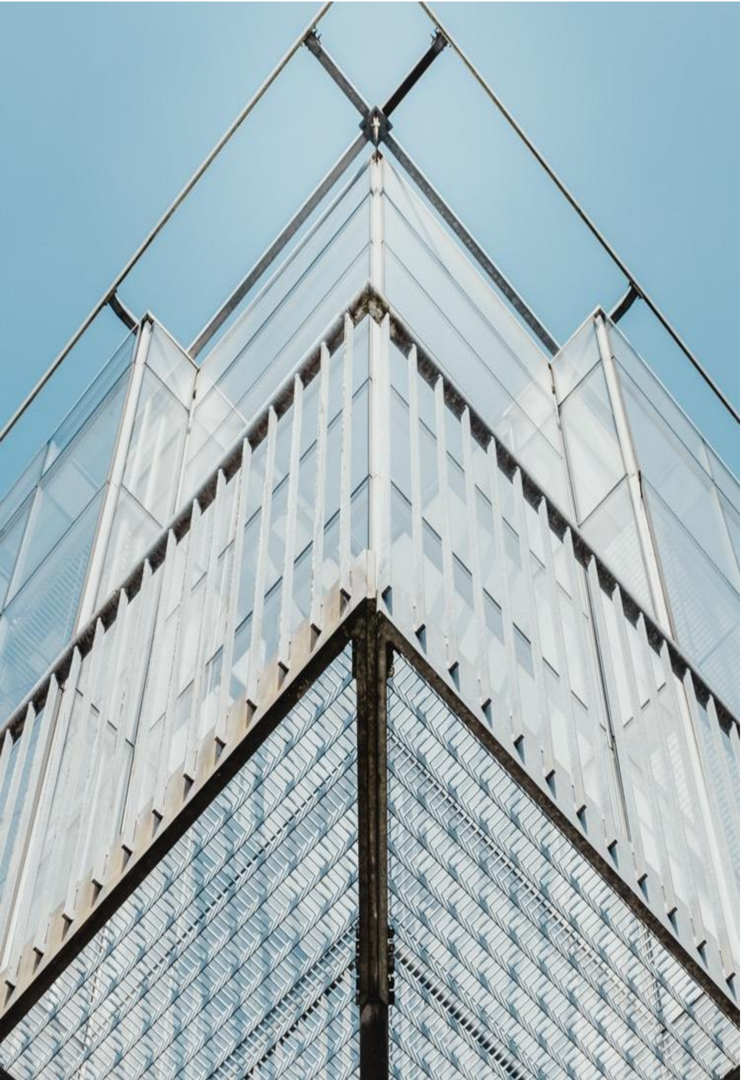




- An underprediction is observed in OOT sample for both Bank Model and FICO A-E Model.
- Greater underprediction at higher loan amounts (where the population is sensitive) is observed for the PD Model compared to the A-E Model as it does not take action sensitivity into account.
- The A-E Model predictions are closer to actual bad rates at higher actions as the model effectively captures sensitivity of riskier population to higher loan amounts.
- While rank ordering prevails for both models, the A-E Model predicts the bad rate trend across amount bands more accurately, observed from the curvature.

Conclusions

- Action Effect Modeling is a 2-step approach to predict target response to action and predictors built upon 20 years of experience modeling causality probabilities.
- Action-Effect captures action sensitivity to make accurate predictions of how the bad rate changes
- Portfolio distribution remains stable between development and OOT. Though, a shift in volumes is observed towards higher loan amount bins.
- An increase in bad rate is observed in the OOT data - This is expected because both observation and performance period overlap with the COVID period (March 2020) onwards.
- While the A-E Model performance has dropped compared to development, it is able to rank-order and capture sensitivity across loan amount bands effectively in OOT data
- While the A-E Model's performance is lower than Bank Model in OOT, it is more efficient at capturing action sensitivity. The Bank Model underestimates risk at high loan amounts for the WalkIn Segment.



FICO

- FICO Optimization Product page (including DO):
  - https://www.fico.com/en/products/fico-xpress-optimization
- Success stories on Credit Card Limit Optimization:
  - https://www.fico.com/blogs/credit-card-portfolio-optimization
  - https://www.fico.com/en/newsroom/hsbc-achieves-15-uplift-monthly-card-spend-using-fico-s-ai-powered-optimization
- FICO Community page: https://community.fico.com/s/optimization

Thank You!