OPTIMAL PATH PLANNING FOR CONSUMER CREDIT SCORE IMPROVEMENT

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Agenda

- Introduction
- Model Development
- Example
- Conclusions
- Questions and Comments

Optimal Paths

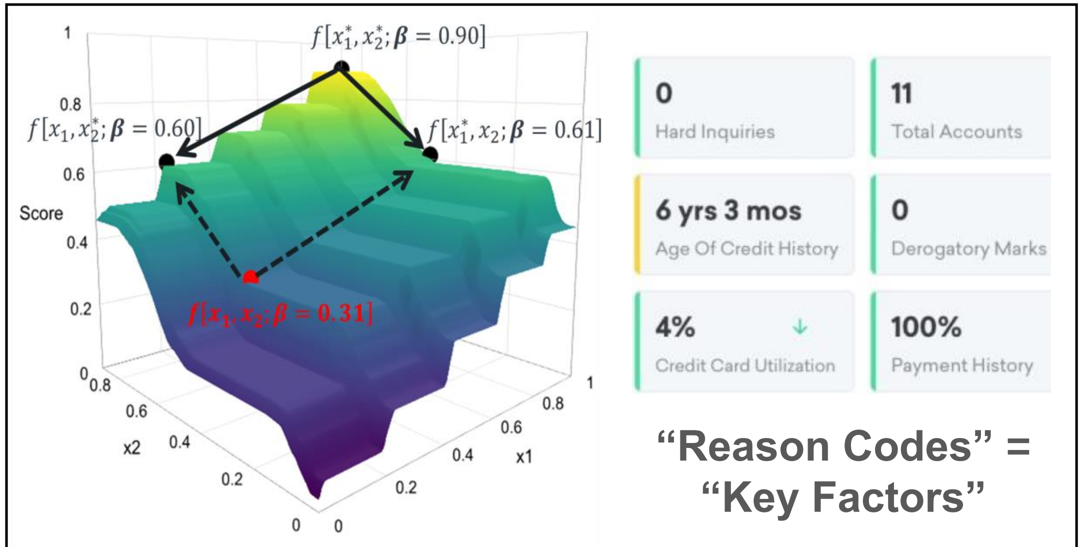
- Increasing expectation on financial institutions utilizing consumer data to *“explain”* how automated systems make decisions
- ML models complicate explanations of “actionable” consumer behavior due to the inherent nonlinearity and interactions present in these models
- Explanations of credit risk models do not necessarily translate into the ordered sequence of actions a consumer could take to improve their score to a desired value

Objective Describe a method for constructing an optimal path that **explicitly navigates an individual consumer through the model feature space** from their current score to a score of their choosing

Explaining Credit Scores

Suppose a consumer desires to reach a given credit score…

- What are the sequence of actions the consumer *should* take to reach the desired score?



"Reason Codes" = "Key Factors"

"What If" Simulators

What *would* happen if an action is taken?

- What if I apply for a new credit card?
- What if I pay off my balance in full?

Reason Codes

Reasons *why* you were denied credit.

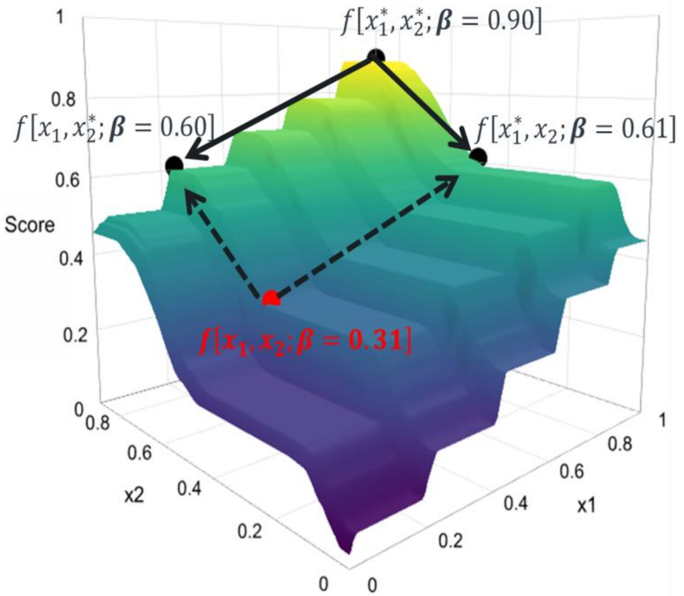
- Too many accounts past due
- Sum of balances on accounts too high

Explaining Credit Scores

"What If"

- Assumes independence of groups of attributes in the model and additivity
- No sense of "feasibility" to the consumer, only portfolio level
  - Can't remove a bankruptcy received last month
  - Reduce $500K mortgage balance to $0

Example of calculating reason codes



Reason codes (generic advice) provide factors most negatively impacting consumers score

- Max Points Lost

Reason Code: $\boldsymbol{x_1}$ $f[x_1^*, x_2^*; \boldsymbol{\beta}] - f[x_1, x_2^*; \boldsymbol{\beta}] = 0.30$

Reason Code: $\boldsymbol{x_2}$ $f[x_1^*, x_2^*; \boldsymbol{\beta}] - f[x_1^*, x_2; \boldsymbol{\beta}] = 0.29$

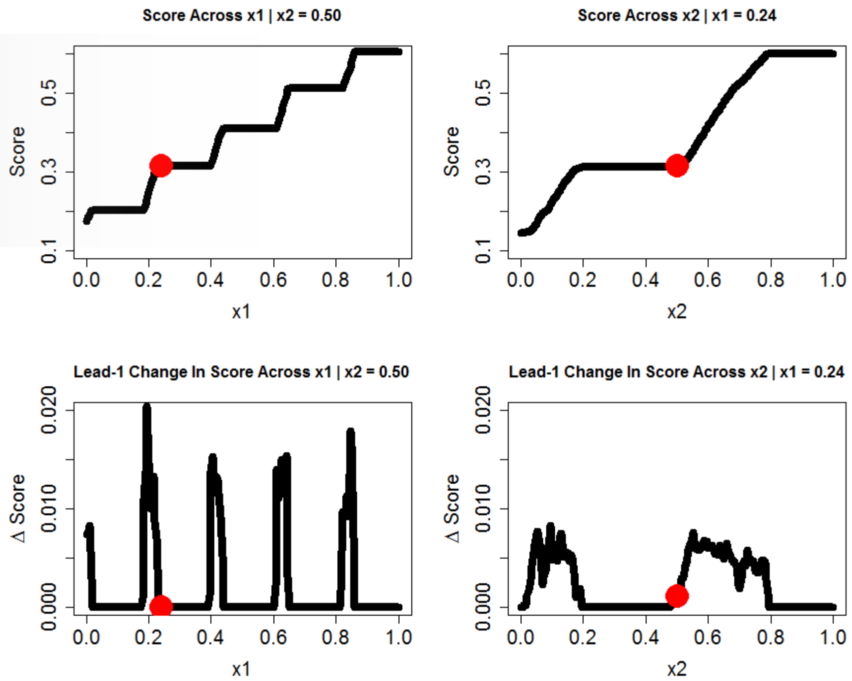
- Points to Max Improvement

Reason Code: $\boldsymbol{x_1}$ $f[x_1^*, x_2; \boldsymbol{\beta}] - f[x_1, x_2; \boldsymbol{\beta}] = 0.30$

Reason Code: $\boldsymbol{x_2}$ $f[x_1, x_2^*; \boldsymbol{\beta}] - f[x_1, x_2; \boldsymbol{\beta}] = 0.29$

Conditional changes in score across

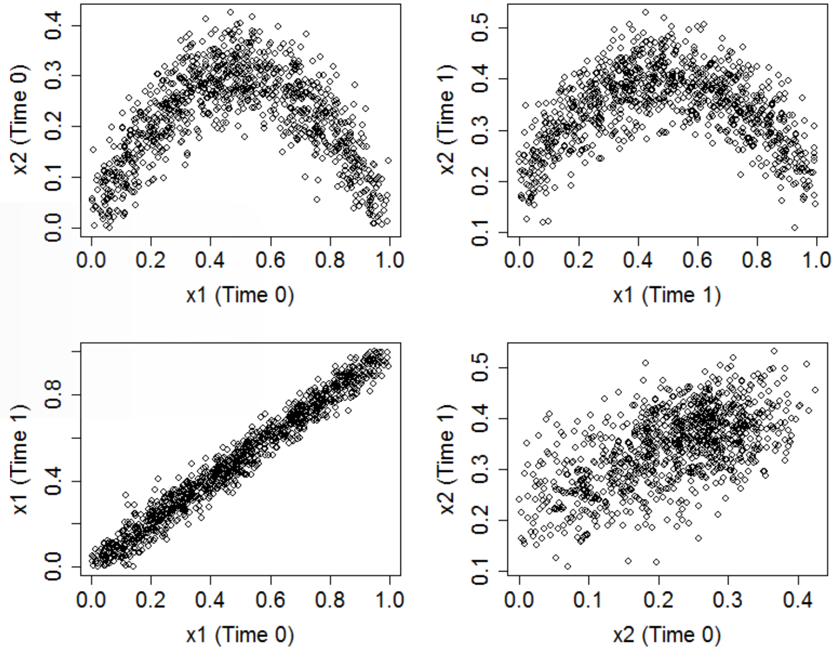
Reason codes do not necessarily indicate the proper order of actions to improve score in the most efficient manner



Explaining Credit Scores

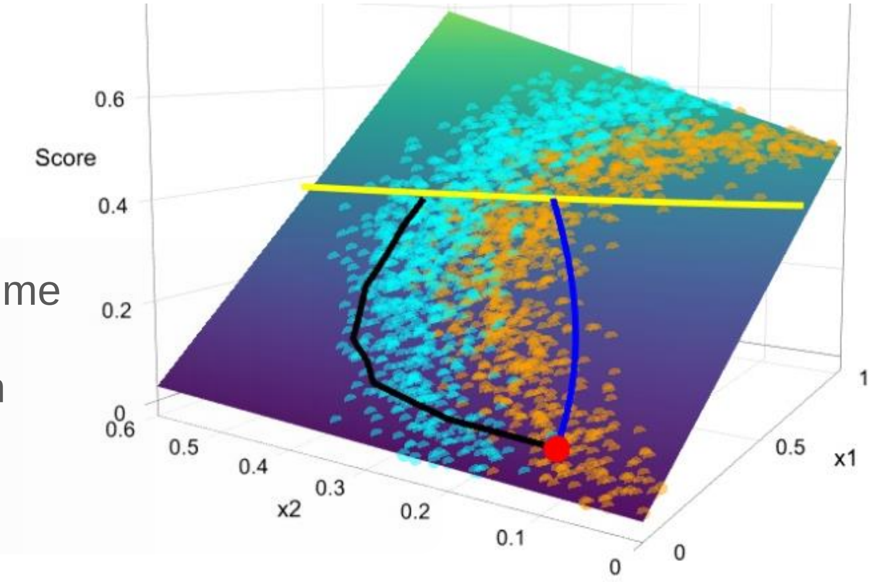
- How do attributes change across *space and time*?
- Every point in the scoring domain may not be feasible to the consumer
- Feasibility needs to account for covariance among attributes over time
- Given an initial starting point $\mathbf{x}^0$ at t^0, we need to find $\mathbf{x}^1 = \mathbf{x}^0 + \boldsymbol{\delta}$ at t^1 with the constraint that $f(\mathbf{x}^1) = C$

Relationships between x_1 and x_2 across time



Gradient descent (blue) and Mahalanobis (black) over time from current score (x^0,t^0 = red dot) to specified score (yellow line) with a score increase of 0.025 units in each time period (orange points = t^0, blue points = t^1)*

$*Score = 1.0x_1 + 0.1x_2 + 1.0x_1x_2$



Seeking Feasibility

Need a metric that captures what movements in the feature space are feasible for a consumer over time, conditioned on their current location $\mathbf{x}^{t_0}$. Let,

$$\boldsymbol{\delta} = \mathbf{x}^{t_1} - \mathbf{x}^{t_0}, \quad \boldsymbol{\mu} = \mathbb{E}(\boldsymbol{\delta}|\mathbf{x}^{t_0}), \quad \boldsymbol{\Sigma} = \mathrm{Cov}[\boldsymbol{\delta}|\mathbf{x}^{t_0}]$$

- $\mathbf{x}^{t_0}$, $\mathbf{x}^{t_1} = p \times 1$ vectors of attributes measured at two time points
- $\boldsymbol{\mu} = p \times 1$ vectors of mean differences of attributes at t_0 and t_1
- $\boldsymbol{\Sigma} =$ covariance matrix of differences of attributes at t_0 and t_1

Constrained Optimization Problem

$$\underset{\delta}{\text{argmin:}} \ (\boldsymbol{\delta} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{\delta} - \boldsymbol{\mu})$$

Subject to: $f(\mathbf{x}^{t_0} + \boldsymbol{\delta};\ \boldsymbol{\beta}) = C$

Equation 1

Equation 1 finds the shortest Mahalanobis Distance (MD) between $\mathbf{x}^{t_0}$ and $\mathbf{x}^{t_1} = \mathbf{x}^{t_0} + \boldsymbol{\delta}$ to achieve a specified score increase

MD accounts for different variances among attributes and covariance between attributes.

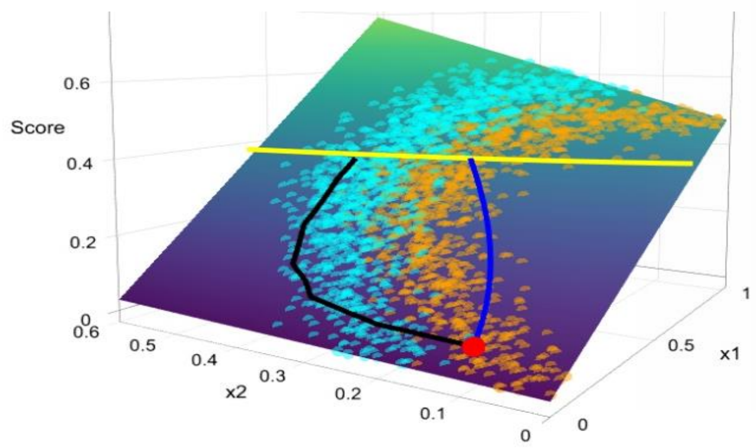
Estimating Feasibility

- Need to estimate $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ across the domain of our feature space
- Using $\mathbf{X}^{t_0}$, partition the feature space into k clusters and estimate the mean $\boldsymbol{\mu}_k$ and covariance matrix $\boldsymbol{\Sigma}_k$ of the delta changes between time t_0 and t_1 per cluster
- Our objective function now becomes:

$$\underset{\delta}{\text{argmin}}: (\boldsymbol{\delta} - \boldsymbol{\mu}_k)^T \boldsymbol{\Sigma}_k^{-1} (\boldsymbol{\delta} - \boldsymbol{\mu}_k)$$

Subject to: $f(\mathbf{x}^{t_0} + \boldsymbol{\delta};\ \boldsymbol{\beta}) = C$

Equation 2 makes explicit that attributes can vary differently across time given a consumer's current location in the domain



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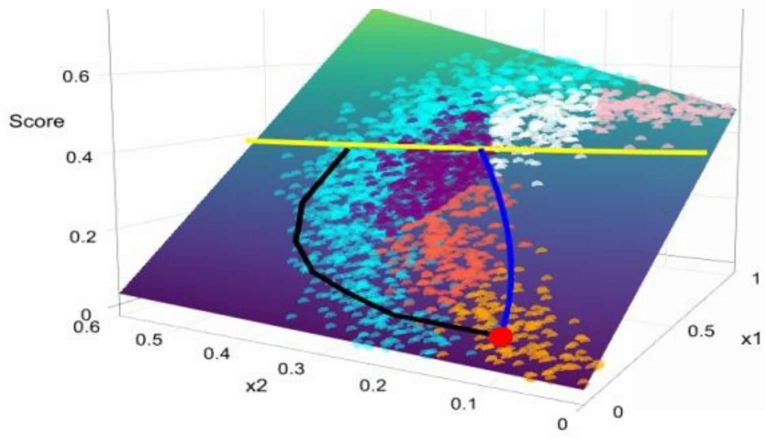


Gradient descent (blue) and Mahalanobis (black) over time from current score (X^0,t^0 = red dot) to specified score (yellow line) with a score increase of 0.025 units in each time period (t^1 = blue points, t_0^k = all other colors)

Optimal Path Algorithm

Algorithm

1. Conduct a cluster analysis on sample data at t_0
2. For each cluster, c_k, Calculate $\widehat{\boldsymbol{\mu}_k}$, $\widehat{\boldsymbol{\Sigma}_k}$
3. Given a consumer with attributes $\mathbf{x}^{t_0}$:
4. **for** $j = 1, \ldots, T$ **do**
   a. Classify consumer with attributes $\mathbf{x}^{t_{j-1}}$ into c_k ← *Equation 3*
   b. $\underset{\boldsymbol{\delta}}{\operatorname{argmin}}$: $(\boldsymbol{\delta} - \boldsymbol{\mu}_k)^T \boldsymbol{\Sigma}_k^{-1} (\boldsymbol{\delta} - \boldsymbol{\mu}_k)$
      Subject to: $f(\mathbf{x}^{t_{j-1}} + \boldsymbol{\delta};\ \boldsymbol{\beta}) = C$
   c. Set $\mathbf{x}^{t_j} = \mathbf{x}^{t_{j-1}} + \boldsymbol{\delta}$
5. **end**

Equation 3 requires mixed-integer nonlinear optimization

Bounds on attributes: (# Inquiries $\geq$ 0) , integer constraints (# inquires)

- **Missing values**
- **Default values**
- **Categorical values**

A Simple Use Case

Sampled 1%
of U.S. consumers

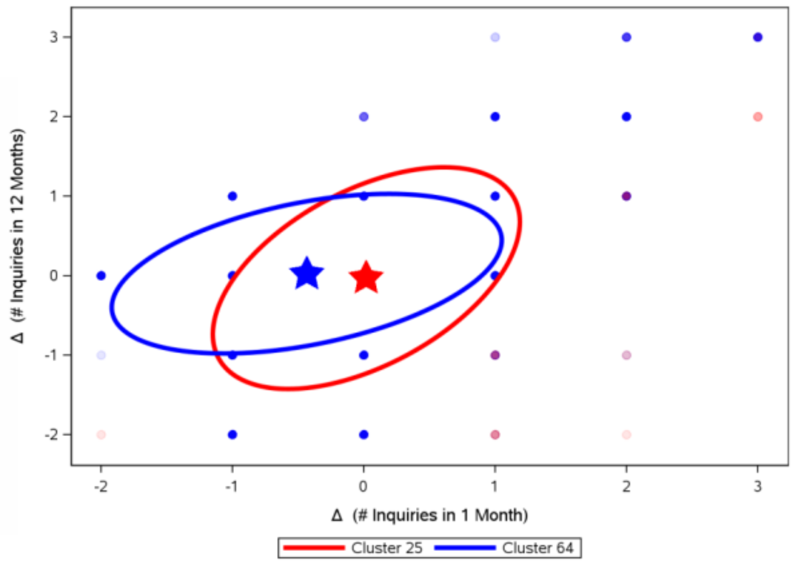
Jan 2018 = t_0
Feb 2018 = t_1

At least one open trade and valid Equifax Risk Score (ERS)

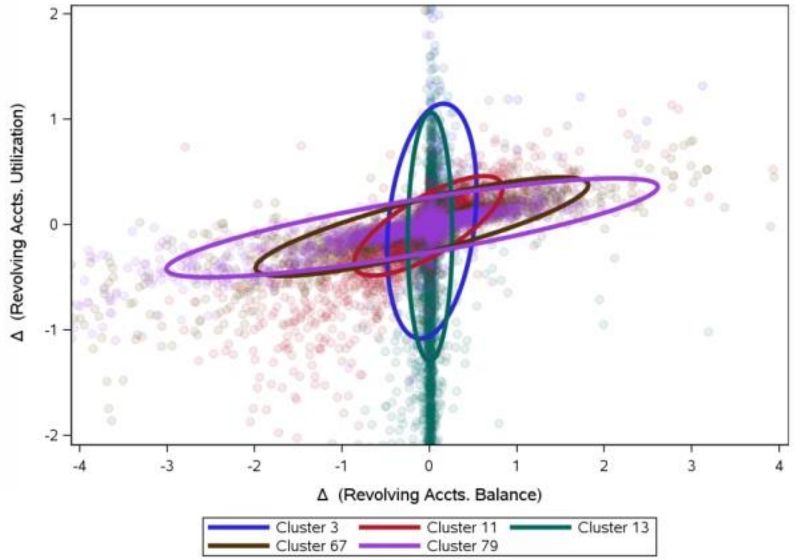
- All attributes were treated as continuous
(only 11 attributes were utilized in this use case)
- Default/Missing values imputed to 0 or 1 as appropriate
- Equifax NeuroDecision: 2-Hidden Layer (10-nodes each layer)
- K-means cluster analysis (100 clusters)

How Far To Walk?

- **95% prediction intervals** ($\boldsymbol{\delta} = \mathbf{x}^{t_1} - \mathbf{x}^{t_0}$) for two clusters (# Inquiries in 1- and 12- months)
- **Red:** No mean change in IQ1 and IQ12. Typical of consumers with no IQ on file or an inquiry between 2- and 11-months
- **Blue:** Mean change in IQ1 but not IQ12. Typical of consumers who have a recent inquiry that rolls off the IQ1 but not IQ12



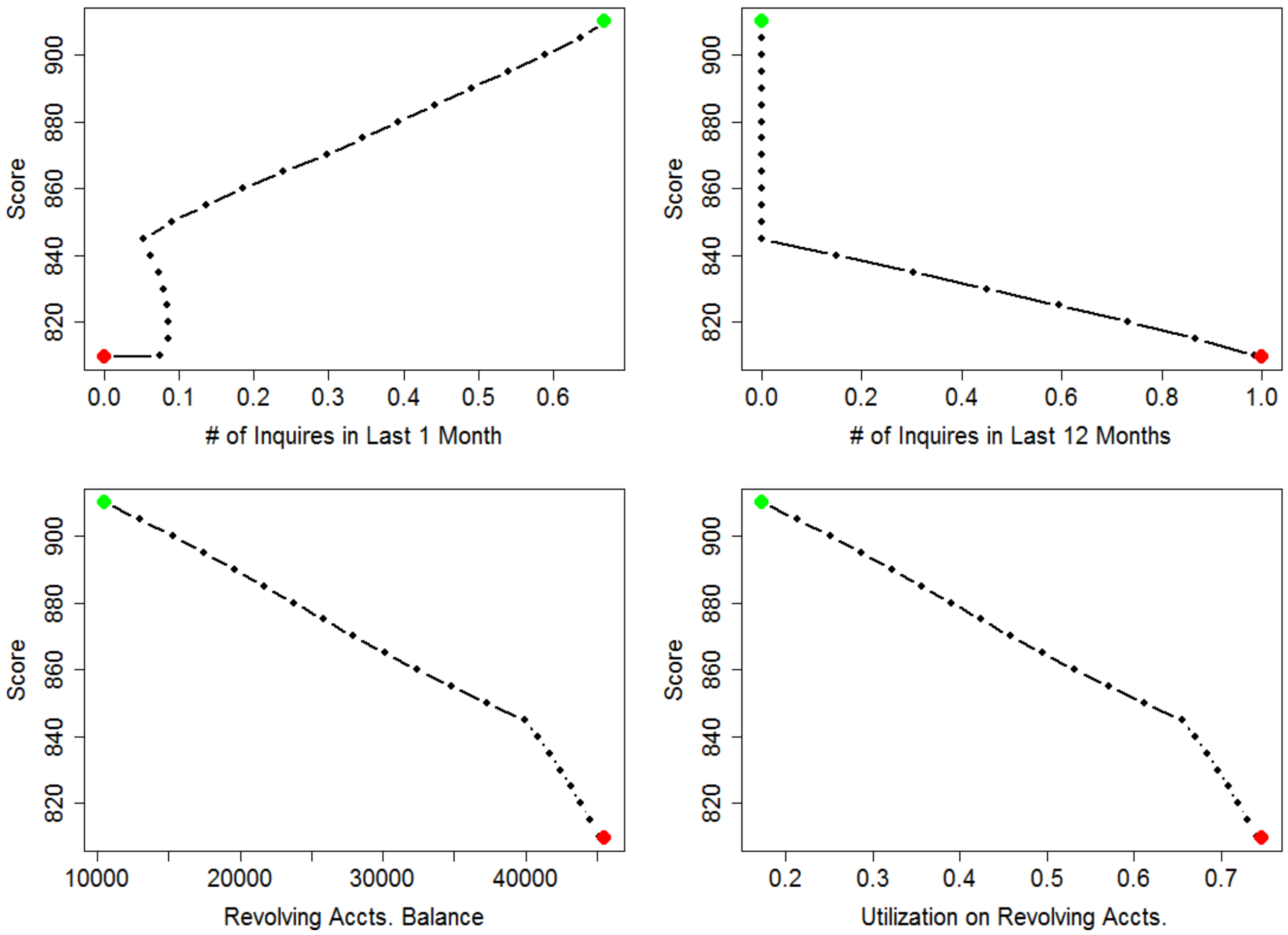
- **95% prediction intervals** ($\boldsymbol{\delta} = \mathbf{x}^{t_1} - \mathbf{x}^{t_0}$) for five clusters (balance and utilization)
- **Green/Blue:** Change in utilization, minimal change in balance. Typical of consumers with newly opened or closed accounts, credit limit increases or decreases, or low credit limits
- **Other colors:** Most clusters exhibit positive correlation: increasing balance increases utilization



Optimal Path For Consumer 1

Consumers goal is to **increase score 100-points** in 5-point increments every month

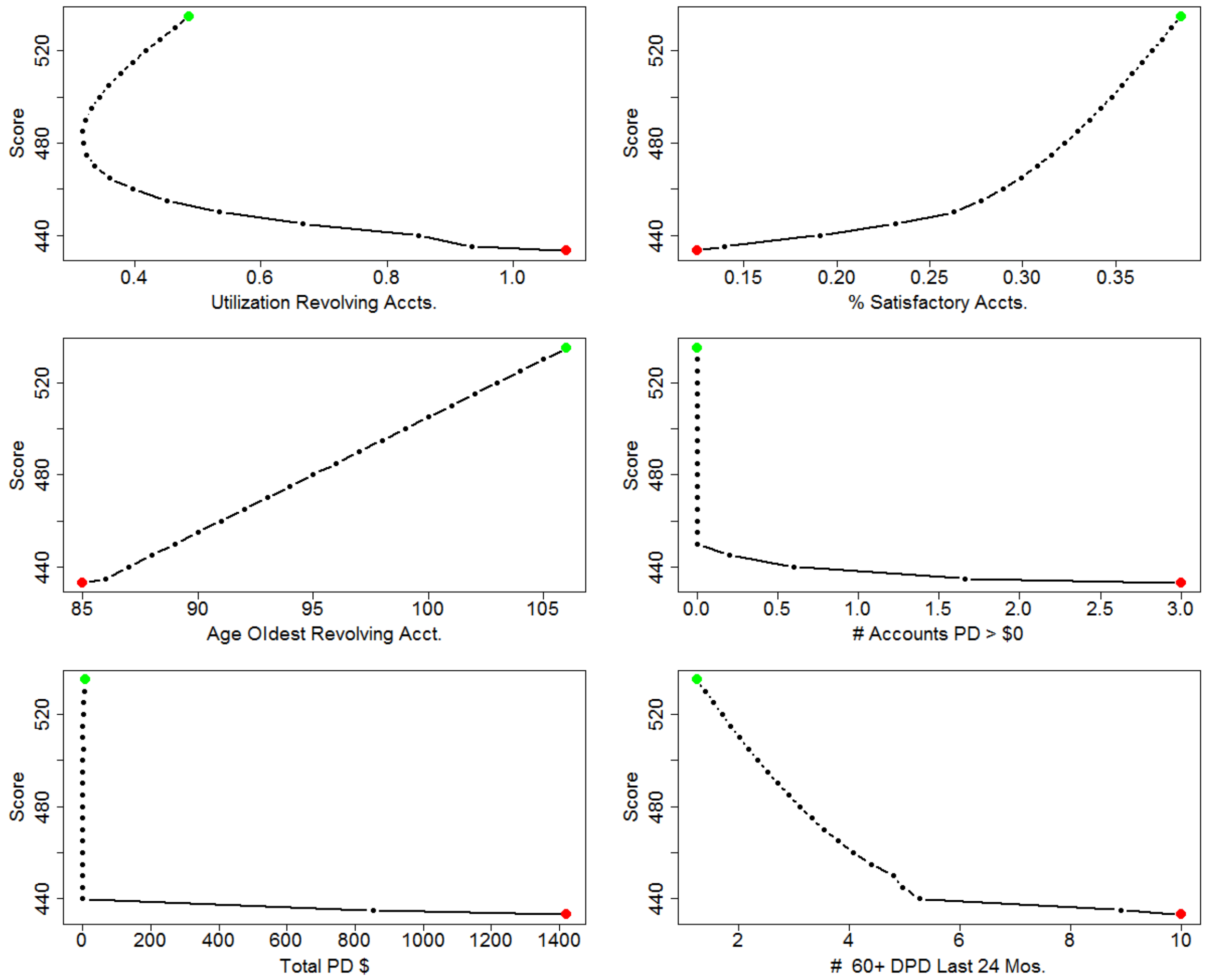
Attribute	t_0	t_{21}
# Inquiries Last Month	0	0.67
Revolving Accts. Balance	$45,500	$10,483
Utilization Revolving Accts.	0.747	0.172
% Satisfactory Accts.	1	1
# Inquiries Last 12 Mos.	1	0
# Accts.	33	33
Age Oldest Revolving Acct.	278	299
# Accounts PD > $0	0	0
Total PD $	$0	$0
# 60+ DPD Last 24 Mos.	0	0
% Revolving Accts. To Total Accts.	0.875	0.890
SCORE	**809**	**910**



Optimal Path For Consumer 2

Consumers goal is to **increase score 100-points** in 5-point increments every month

Attribute	t_0	t_{21}
# Inquiries Last Month	0	0.38
Revolving Accts. Balance	$542	$243
Utilization Revolving Accts.	1.0	0.48
% Satisfactory Accts.	0.12	0.38
# Inquiries Last 12 Mos.	3	1.1
# Accts.	8	7.6
Age Oldest Revolving Acct.	85	106
# Accounts PD > $0	3	0
Total PD $	$1421	$7.2
# 60+ DPD Last 24 Mos.	10	1.25
% Revolving Accts. To Total Accts.	0. 5	0.5
SCORE	**433**	**535**



Conclusions

- Most credit score simulators are limited in available actions and are “trial and error” based
- Reason codes do not necessarily indicate the proper order of actions to improve a consumers score in the most efficient manner
- Our algorithm generates an optimal path that is feasible for a consumer in monthly increments
  - Our algorithm accounts for within-subject changes in attributes over space and time
- The optimal paths algorithm provides feasible, actionable, and impactful recommendations to the consumer

Questions & Comments

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