The Power to Know.

Credit Limit Optimization (CLO) for Credit Cards

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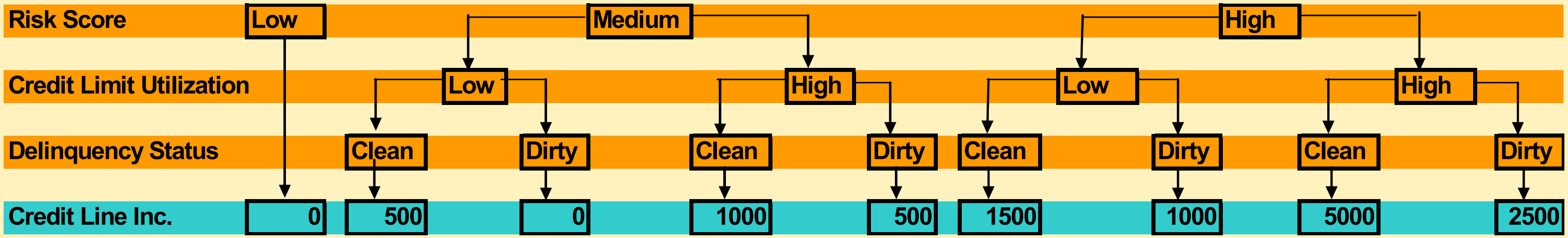
Agenda

- Background
  - Traditional approaches to credit limit management
  - History of different products/approaches
- Characteristics of the ideal solution
- Approaches to problem formulation
- Building good action-effect models
- Optimization problem
- Challenges in deploying the solution
- Optimization in other areas of credit card industry
- Q and A

Historical Credit Limit Change Programs



- Implemented in the form of decision trees/strategies
- Champion/Challenger framework for improving strategies over time
  - Randomly assign accounts to champion or challenger strategy
  - Measure performance over time
- Takes a six to twelve months to evaluate each challenger strategy
- A very small number of potential champion strategies can be tested at a given time
- Difficult to analyze why a particular challenger strategy worked

Efforts to Improve Credit Line Decisions

- By internal modeling groups of large banks
  - Optimization (e.g., JP Morgan Chase)
  - Markov decision processes (e.g., Bank One)
- By vendors
  - Greedy algorithms
  - Analytics heavy approaches
  - Optimization heavy approaches
  - Deterministic optimization
  - Robust optimization

Characteristics of Ideal CLO Solution

- Identify an optimal solution without lengthy champion/challenger iterations
- Achieve the full potential of each and every account relationship, not some segment level abstraction
- Optimize specific campaign goals such as profit or revenue or balance
- Accommodate operational as well as business constraints
- Factor in uncertainty in estimates and environment
- Examine multiple scenarios before committing to a final course of action
- Easy to deploy solutions
- Experimental design to explore new areas

Components of CLO Solution

- Data
- Action-Effect models
- Optimization
- Deployment
- Evaluation

Data Requirements for CLO

- Actions related data
  - Data from past campaigns
  - Results from systematically designed experiments
- Behavior related data
  - Statement data
  - Authorizations
  - Payments
  - Call-center data
- Organizational data
  - Business constraints data
  - Operations constraints data
- External data
  - Bureau data
  - Marketing data

Expanding Beyond the “Comfort Zone”

Risk Score	Low	Medium				High			
Credit Limit Utilization		Low		High		Low		High	
Delinquency Status		Clean	Dirty	Clean	Dirty	Clean	Dirty	Clean	Dirty
Champion Credit Line Inc.	0	500	0	1000	500	1500	1000	5000	2500
Test Group 1	0	0	0	500	0	500	0	2500	1000
Test Group 2	0	0	0	500	0	1500	0	3000	1500
Test Group 3	0	0	0	1500	0	2000	1500	4000	2000
Test Group 4	500	1000	500	2500	1000	3000	2000	7000	3000
Test Group 5	500	1500	1000	3000	1500	4000	2500	8000	4000
Test Group 6	500	2000	1500	4000	2500	5000	3000	9000	5000

- Use Design of Experiments concepts
  - Generate the most amount of information at lowest cost
- Necessary to explore regions never tested before
  - e.g., increases for accounts with risky scores, higher increases for low risk accounts
- Necessary to build better action-effect models
- Help respond to competitive pressures or more aggressive business goals

Randomized Block Design Details

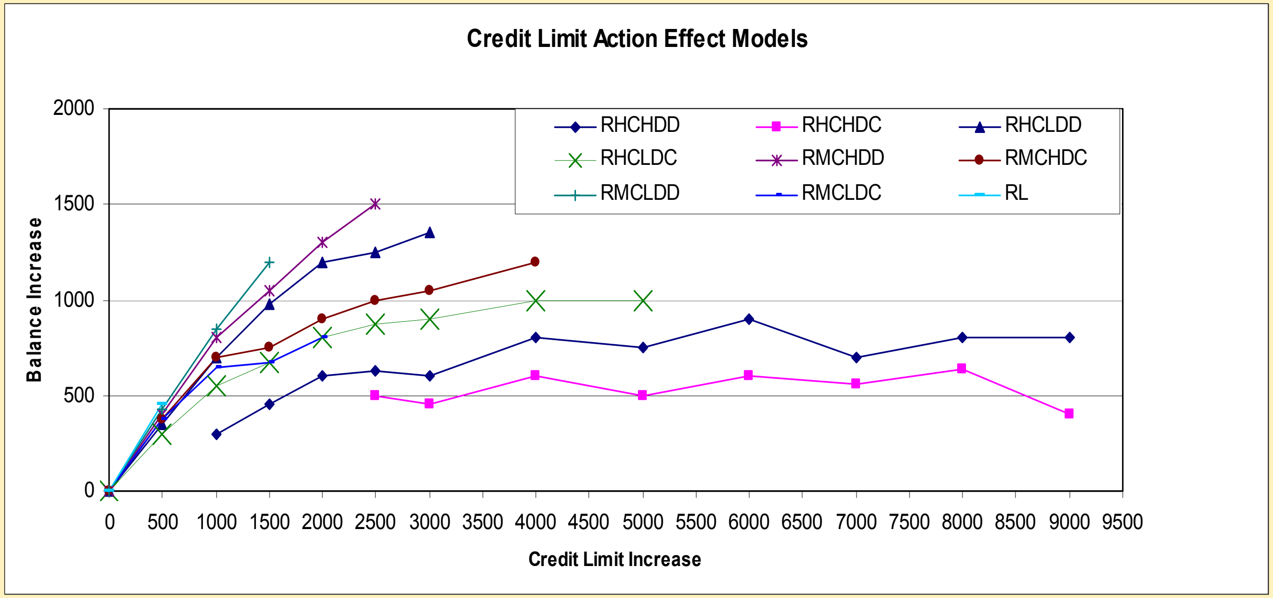
- Response variable: Change in balance over a 6 month period.
  - Could be credit risk, attrition risk, revenue
- Treatment levels (500,1000, 1500, 2000, 2500, 3000, 4000, 5000, 6000, 7000, 8000, 9000)
  - More levels allows one to explore a wider space
- Blocks (RL, RMCLDS, RMCLDD, RMCHDC, RMCHDD, RHCLDC, RHCLDD, RHCHDC, RHCHDD)
  - Blocking helps group similar accounts together reducing variation
  - Treatments within blocks randomly assigned
  - Blocking allows block versus treatment interaction
- Incomplete blocks, i.e., not all treatments repeated in all blocks due to business reasons
- Unbalanced design, i.e., each treatment does not appear the same number of times in each block

Action-Effect Models for CLO

- Use influence diagrams to visualize problem
- Predict effect of change in credit line on credit risk, attrition risk, revenue, and profit
- Segmentation choice crucial
  - Use the same segments as credit risk models
  - Use same segments as credit strategy
  - Using different segmentation in later stages could be problematic
- Accuracy of action-effect models determine the validity of optimization results

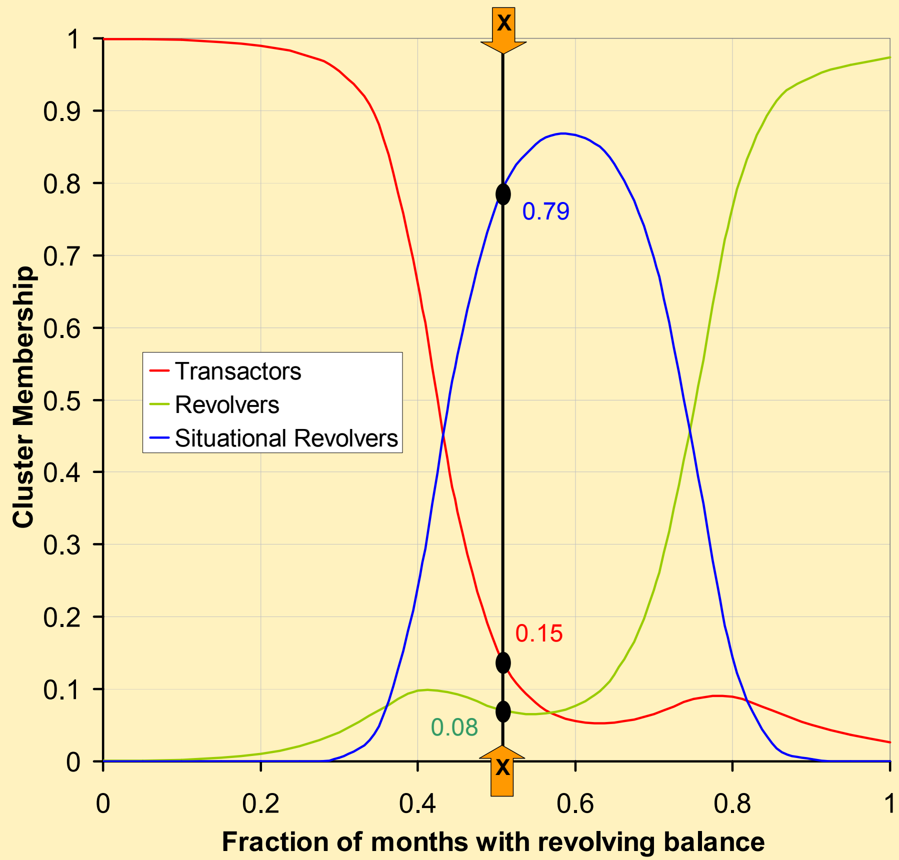
Data for Action-Effect Models

- Response is non-linear
- Low risk segments close to saturation point
- High risk segments show better response to increases
- Similar curves for credit risk and attrition risk



Enhancing Data for Action-Effect Models

- Traditional clustering: each data point assigned to a single class
  - Manual: segmentation, e.g. age
  - Data-driven: k-means
- Soft clustering: each data point belongs to all clusters in graded degree
  - Cluster membership determined by distance from center.
  - Data-driven: Cluster centers and shape updated intelligently
- Soft-clustering allows same account to be used in multiple action-effect models



Cluster Scoring

- Action-effect models:
  - Build models for change in credit risk, attrition risk, transaction volume and revolving balance, given a credit limit increase using account level information
  - Separate set of models for each segment or group of segments
  - Likely to be nonlinear models
- Scoring:
  - Score each individual account
  - Predict the effects (credit risk, attrition risk, profit/revenue, etc.) of the action/treatment (increase in credit limit)
  - Feed the results as coefficients into the optimization module
- Other inputs for predicting profits/losses:
  - Factors that go into calculating the predictions definable by the user including fixed cost per account for calculating profit, interchange fee, interest rate, late fees, annual fees, and over-limit fees

Optimization Problem Formulations

- Non-linear programming formulations (A)
  - Accounts for non-linear response to credit line increases
  - Even the simplest formulations are difficult to solve
- Linear programming formulations (B, C)
  - Only possible formulation at account level
  - Solutions might be difficult to interpret and deploy
  - Ignores uncertainty in coefficients
- Robust optimization formulations (D)
  - Takes uncertainty into account
- Markov decision processes (E)
  - Allow multiple credit line increases

Non-Linear Programming Example (A)

$$
\begin{aligned}
&Max && \sum_i f(x_i) \\
&s.t. && \sum_i x_i \le B \\
& && \sum_i g(x_i) \le L \\
& && \sum_i f(x_i) \ge (1+R)\sum_i x_i \\
& && x_i \ \ \ge 0
\end{aligned}
$$

where x_i are the credit limit increases,
$f(x_i)$ is the profit for a given increase,
$g(x_i)$ is the loss for a given increase,
B is the total credit increase budget,
L is the total allowable losses, and
R is the hurdle rate

- Credit limit increases are a continuous variable
- Randomly choose a small number of accounts for optimization
- Use Lagrangian relaxation techniques
- Adding more constraints can solution more difficult
- Map optimal solution to a decision tree to score all accounts
- Deploying decision tree in lieu of solution can result in significant loss in benefit of the whole effort

Linear Programming Example I (B)

$$
\begin{aligned}
&Max \quad \sum_j \sum_i p_{ji} x_{ji} \\
&s.t. \quad \sum_j c_j \sum_i N_i x_{ji} \le B \\
&\qquad \sum_j \sum_i l_{ji} x_{ji} \le L \\
&\qquad \sum_j \sum_i p_{ji} x_{ji} \ge (1+R)\left(\sum_j c_j \sum_i N_i x_{ji}\right) \\
&\qquad \sum_j x_{ji} = 1 \forall i \\
&\qquad x_{ji} \in \{0,1\}
\end{aligned}
$$

where x_{ji} is 1 if account i is given credit line c_j

p_{ji} is the profit for a given increase, and

l_{ji} is the loss a given increase

- Only discrete credit limit increases allowed
- Subset of LP problem has integer solutions most of the time
- Account level optimization possible
- Solve relaxed LP problem and check feasibility for remaining constraints
- No need to map optimal solution to a score

Linear Programming Example II (C)

$$\begin{aligned}
&Max \quad \sum_t \sum_j \sum_i p_{tji} x_{ji} \\
&s.t. \quad \sum_j c_j \sum_i N_i x_{ji} \le B \\
&\sum_t \sum_j \sum_i l_{tji} x_{ji} \le L \\
&\sum_t \sum_j \sum_i p_{tji} x_{ji} \ge (1+R)\left(\sum_j c_j \sum_i N_i x_{ji} \right) \\
&\sum_j x_{ji} = 1 \text{ for each } i \\
&1 \ge x_{ji} \ge 0
\end{aligned}$$

where x_{ji} are the fraction of accounts in segment i
with credit limit increase c_j,
p_{tji} is the profit in time period t for a given increase, and
l_{tji} is the loss in time period t for a given increase

- Only discrete credit limit increases allowed
- Segment level optimization
- Random fraction of accounts in a segment get a particular increase
- No need to map optimal solution to a score
- Predicting profits and losses over multiple time periods difficult

Robust Optimization Example (D)

$$
\begin{aligned}
Max \quad & \sum_k \left(\sum_t \sum_j \sum_i p_{ktji} x_{ji} \right) \Big/ M \\
s.t. \quad & \sum_j c_j \sum_i N_i x_{ji} \le B \\
& \sum_t \sum_j \sum_i l_{ktji} x_{ji} \le L \;\forall\; k \\
& \sum_t \sum_j \sum_i p_{ktji} x_{ji} \ge (1+R) \left(\sum_j c_j \sum_i N_i x_{ji} \right) \forall\; k \\
& \sum_j x_{ji} = 1 \text{ for each } i \\
& 1 \ge x_{ji} \ge 0
\end{aligned}
$$

where x_{ji} are the fraction of accounts in segment i with credit limit increase c_j, p_{ktji} is the profit for simulation k for a given increase, and l_{ktji} is the loss for simulation k for a given increase

- Perform M simulations to reflect uncertainty in profit and loss coefficients
- Objective function is an expected value
- Loss and hurdle rate constraints might not be satisfied for all scenarios
- Realized profit and loss values more likely to match optimization solution values

Markov Decision Processes Example (E)

$$V_t(c,i) = \begin{cases} \max\limits_{c_j} \left\{ r(c \pm c_j, i) + \beta \sum\limits_l p(c \pm c_j, i; l) V_{t+1}(c \pm c_j, l) \right\} & \text{if } t = \text{update epoch} \\ r(c,i) + \beta \sum\limits_l p(c,i;l) V_{t+1}(c,l) & \text{otherwise} \end{cases}$$

$$V_T(c,i) = r(c,i)$$

where the account has credit line c, is in one of the segments i,

single period profit is $r(c,i)$,

the transition matrix is $p(c,i\ ;\ l)$,

the value function is $V_t(c,i)$, the time horizon is T, and

the one-period discount factor is β

- Multiple credit line increases over time horizon T
- Takes uncertainty into account
- Can still include constraints, e.g., hurdle rate
- Curse of dimensionality, e.g., 20 treatments and 9 segments gives 180 states, 32,400 cell transition matrix
- Markov assumptions might be violated, e.g., new accounts, balance transfers, other treatments

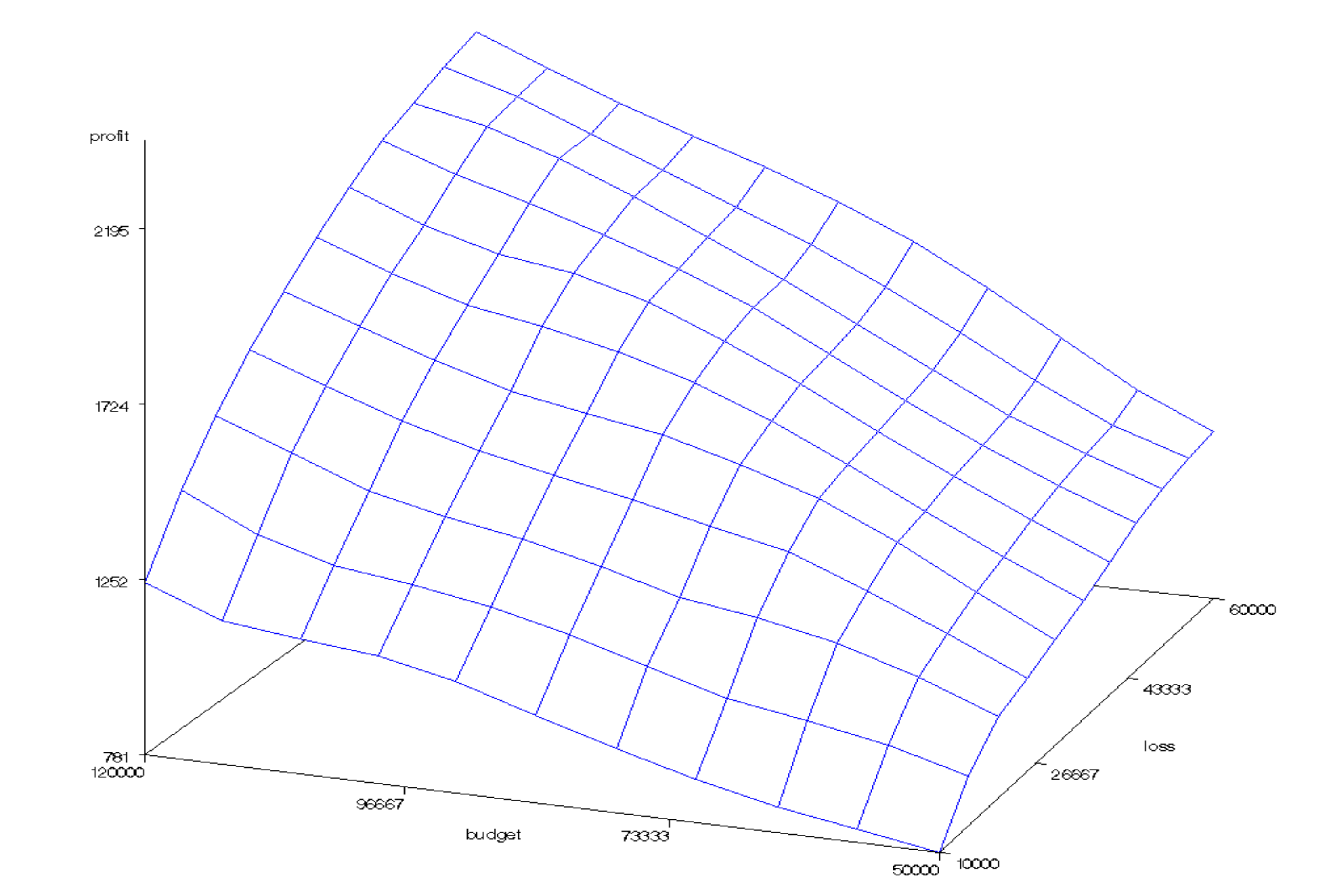
Optimization Formulations Critique

- (A) maintains the non-linear nature of response to credit line changes, and continuous change in credit limits.
  - Useful for testing to what extent discretizing the search space in (B-E) results in suboptimal solutions
- (B) is the only formulation with possible account level optimization, albeit after ignoring some constraints.
  - Useful for testing to what extent sampling (A) and segment level search (C-E) results in suboptimal solutions
- (D) only formulation that take into account the uncertainty in profit as well as loss in response to decisions
  - Useful for testing the impact of uncertainty
- (E) only formulation that takes into account multi-period decision making. (C-D) look at multi-period profits and losses, but do not allow multiple credit line changes
  - Useful for testing the value of multiple credit line changes

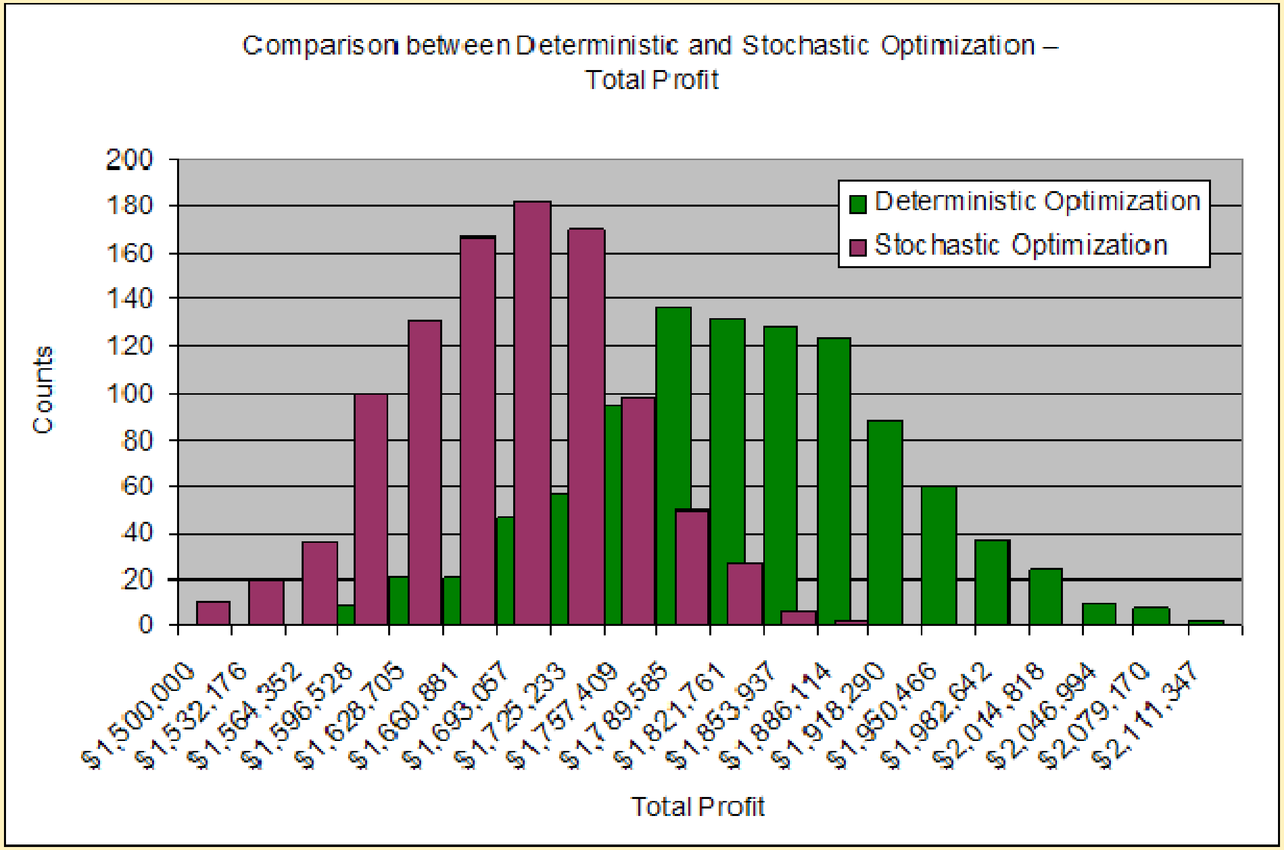
Optimization Formulations Experience

- Accurate estimation of coefficients crucial
  - Inaccuracies can completely negate the optimization approach
  - Design of experiments to collect additional data extremely useful
  - Using all data sources, including transactional data, extremely useful in building more accurate models
- Accounting for uncertainty crucial
  - Realized profits and losses in production much closer to those predicted by robust optimization as compared to deterministic optimization
  - Also important to take into account correlations between all sources of uncertainty
- Segmentation scheme crucial
  - Impacts accuracy of action-effect models
  - Impacts search space explored
- SAS solution does all of the above

Profit Frontier

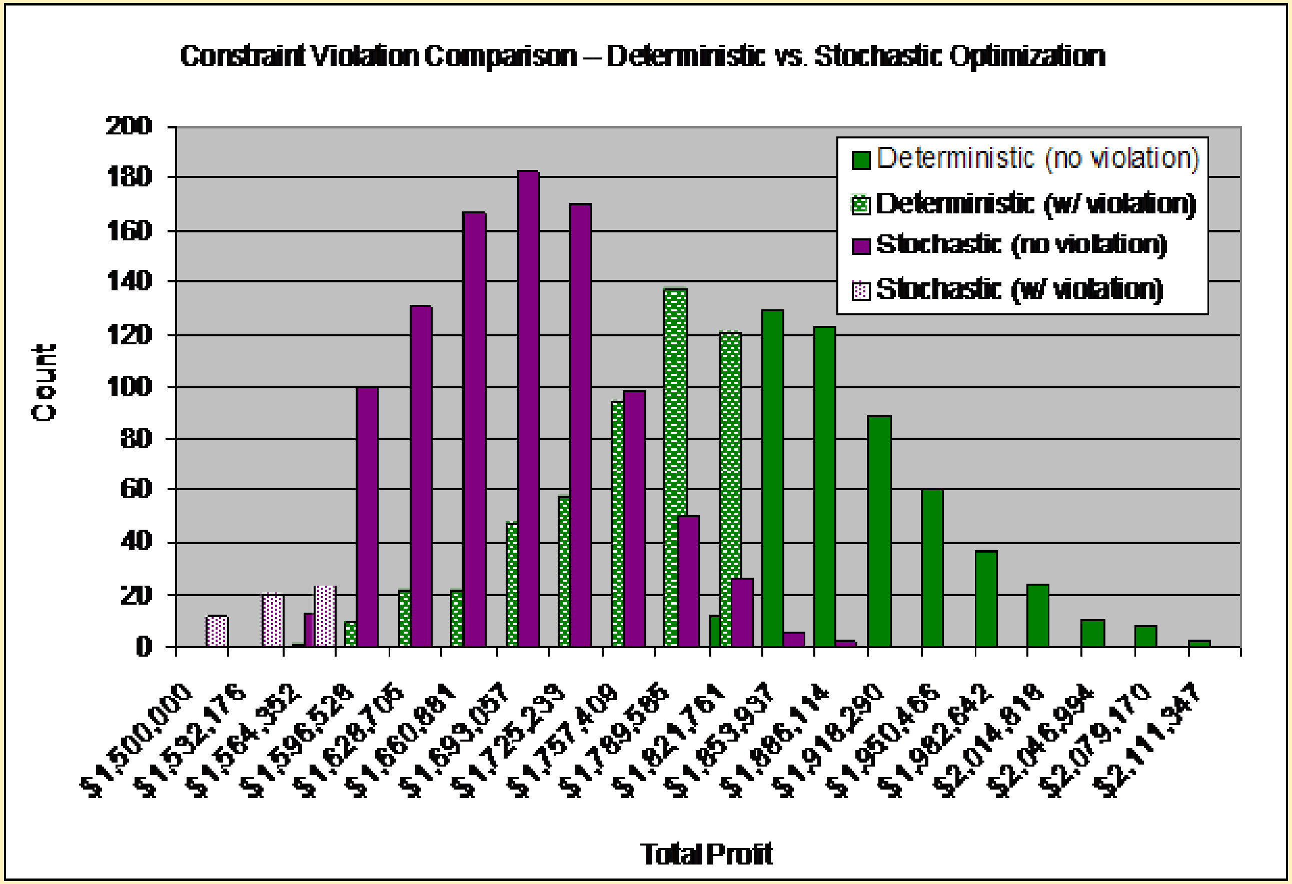


Impact of Uncertainty on Objective Function



- D.O. generates higher expected total profit.
- D.O. has much wider spread when evaluated w/ various scenarios.
- S.O. generated smaller total profit, but higher profit per account.
- S.O. generates a tighter distribution overall
- Results from S.O. gets better as the variance in the parameters increases

Impact of Uncertainty on Constraints



- S.O. is more robust than D.O.
- When simulated w/ various scenarios based on the covariance structure in the coefficients,
  - D.O. violates the constraints in 51% of the out-of-sample evaluations.
  - S.O. violates the constraints 5.5% of the simulation.

Deployment Options for CLO

- Optimization solution output deployed as a list of account numbers with recommended credit limit changes
  - Does not dilute the optimization results
  - Difficult to use in many situations, e.g., production system constraints, accounts not included in the optimization exercise
- Optimization solution used to create a decision tree. Decision tree deployed to score all accounts and determine credit limit changes in production
  - Mapping solution to decision tree can significantly dilute the results
  - Only option when optimization done for a small sample of accounts, or if accounts were not included in the optimization exercise
  - Easier to compare with traditional approaches, or fit into a champion/challenger methodology

Evaluation for CLO

- Important to close the loop
  - Compare production and modeling results
  - Compare results with older strategies
- Use results for planning
  - Use results to collect new data and fill more gaps
  - Interactions with other treatments, loss forecasting

Q & A

- Thank you for the opportunity to present