Enhancing financial risk management with reinforcement learning

Discussion paper

EY
Building a better working world

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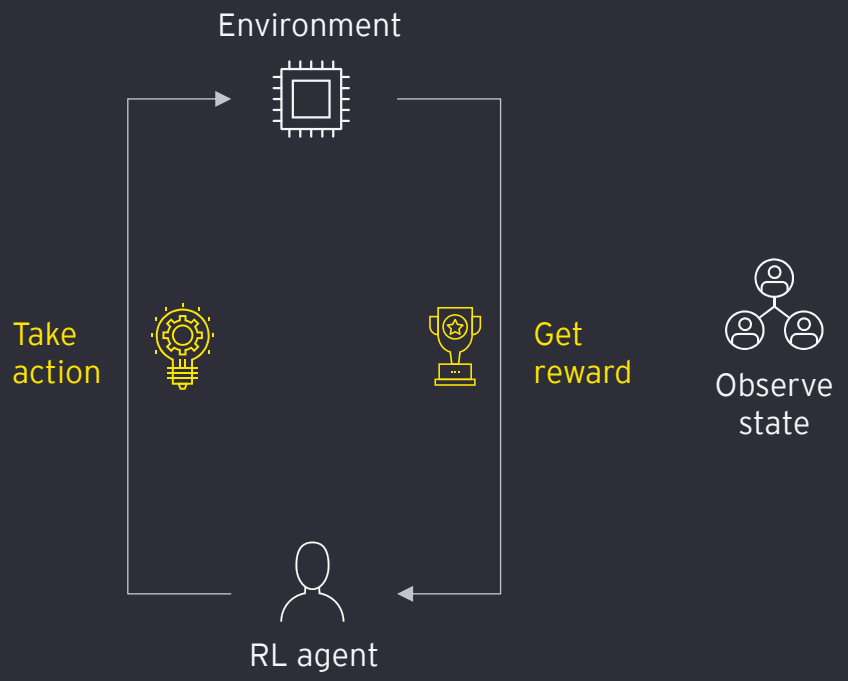
Executive summary

What is reinforcement learning?

Reinforcement learning (RL) is a type of machine learning technique that enables an agent to learn in an interactive environment by trial and error using feedback from its own actions and experiences.



Decision-making process

- **RL agent as decision maker:** It aims to learn the best course of action within an environment to accumulate the highest possible reward.
- **Trial-and-error data accumulation:** RL systems gather data through a process of experimentation, distinct from the data input methods used in supervised or unsupervised learning.

Algorithmic learning and feedback

- **Adaptive algorithms:** RL algorithms learn from the results of their actions, adjusting their strategy to improve outcomes.
- **Feedback loop:** After each action, the algorithm receives feedback signal (i.e, reward) that indicates the effectiveness of its decision, guiding future choices. The reward can be positive (reinforcing the action) or negative (discouraging the action).

Reinforcement learning: characteristics and adaptive applications

Reinforcement learning (RL) systems autonomously master tasks by trial and error, aiming to maximize rewards and make rapid, independent decisions.

Self-teaching mechanisms

RL systems are autonomous, developing their capabilities through a process of trial and error.

Goal-oriented learning

The primary objective is to perform actions that lead to the maximization of rewards, embodying a "learning by doing."

Automated decision-making

RL is ideal for systems requiring numerous, rapid decisions without human intervention.

When does RL add value in complex environment?

- When an environment model is known but lacks an analytic solution.
- Using simulation-based optimization when only a simulation model is available.
- Interacting with the environment directly is the sole method for information gathering.

Robotics

Automating industrial tasks with robots that can adapt to varying conditions and improve efficiency.

Education

Developing personalized training systems that adapt to the learning pace and style of students.

Strategic games

Informing decisions in games like chess, where planning and anticipation of opponent moves are critical.

Process control

Adjusting parameters in real-time for complex systems like petroleum refineries to optimize performance.

How can RL help financial institutions manage risk?

1 PORTFOLIO MANAGEMENT WITH RISK ASSESSMENT

Risk management

By learning the dynamics of market risk, RL can help in devising strategies that dynamically adjust the portfolio to maintain the desired level of risk exposure.

2 CREDIT RISK

Collection strategies

RL can determine the best strategies for loan collections by learning which actions lead to successful repayments without harming customer relationships.

3 FRAUD RISK

Suspicious activity detection

RL can improve the detection of suspicious activities by learning to identify patterns indicative of fraud, reducing false positives and focusing on high-risk transactions.

Data quality valuation

Data is essential for all models. However, noisy and low-quality data may worsen the performance of an algorithm. In this respect, one needs to determine the most useful data for the target task.RL can be used to learn which data is most valuable by looking at how well it does on a specific task. This suggested method is much better than older methods like Leave-One-Out, which judges how important a piece of data is by seeing how the performance changes if that piece is taken away.

Resource: https://arxiv.org/abs/1801.05532

Yuanfei Cui and Fengtong Yao, "Integrating Deep Learning and Reinforcement Learning for Enhanced Financial Risk Forecasting in Supply Chain Management," Springer Link, April 8, 2024

Selected success story: reinforcement learning-enabled collections

RI-enabled collections proof of concept overview

An adaptive, customer-centric, and cost-optimized collections strategy can deliver an 8-10% reduction in charge-off/write-off

Opportunity

Risk-based collection strategies are not efficient

- Collections treatments are traditionally assigned using customer risk categories (high / med / low).
- Outcomes of treatments, costs, and relative benefits of alternative treatments are not considered.
- Current approach creates inefficiencies in use of call centre resources and leads to sub-optimal recovery.

Core concept

An adaptive strategy based on customer behaviour

- Automatically learn the best strategy over time.
- Learn from the outcome of prior treatment attempts.
- Quantify the additional gain from changing a treatment.
- Produce a customized strategy for each customer.
- Adapt as external factors change.

Benefits

Continuously optimized treatment strategy

- Loss reduction: maximize the repayment amounts.
- Improved resource allocation: direct resources to where they will have the highest return.
- Continuous learning: incorporate new information gained from each treatment attempt into future treatment strategies.

Proof of concept results

Annual loss reduction ~$2.5m

8% reduction in charge-off/write-off

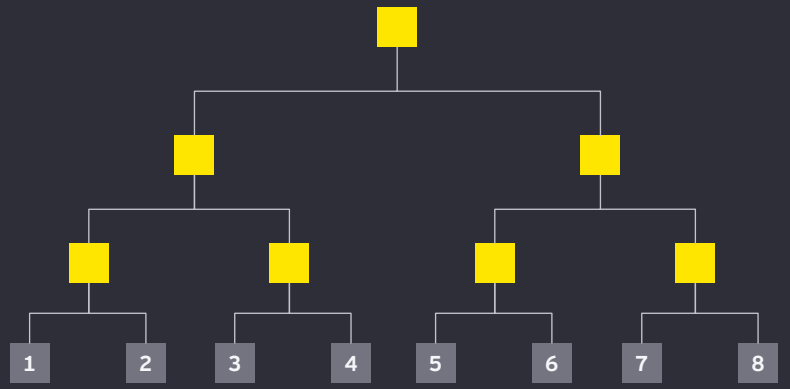
Annual operational savings ~$0.5m

Annual loss reduction ~$2.5m

Collections current approach at a large financial institution

Certain financial institutions use a decision-tree or rule-based collections model targeting risk category

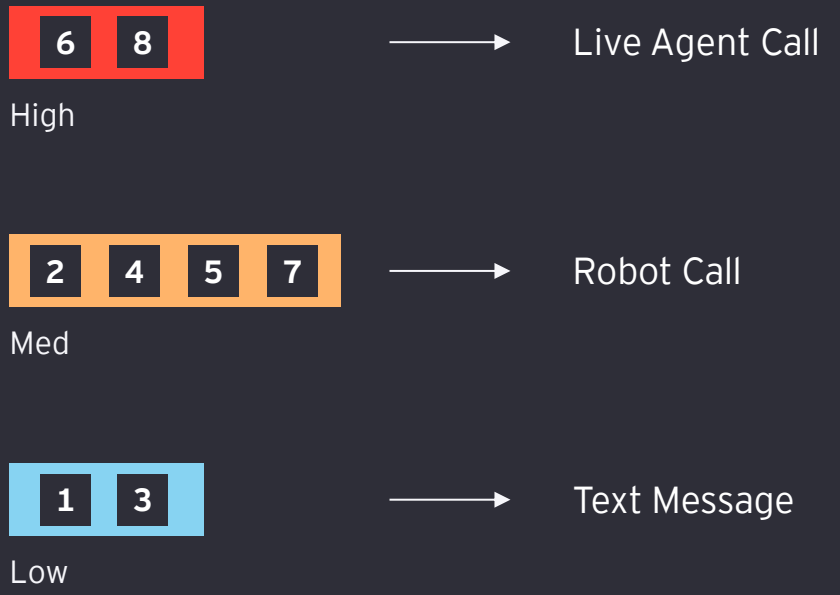
1 Segment accounts along risk factors



2 Bucket segments into broad categories

Low Med High

3 Assign treatment based on risk category

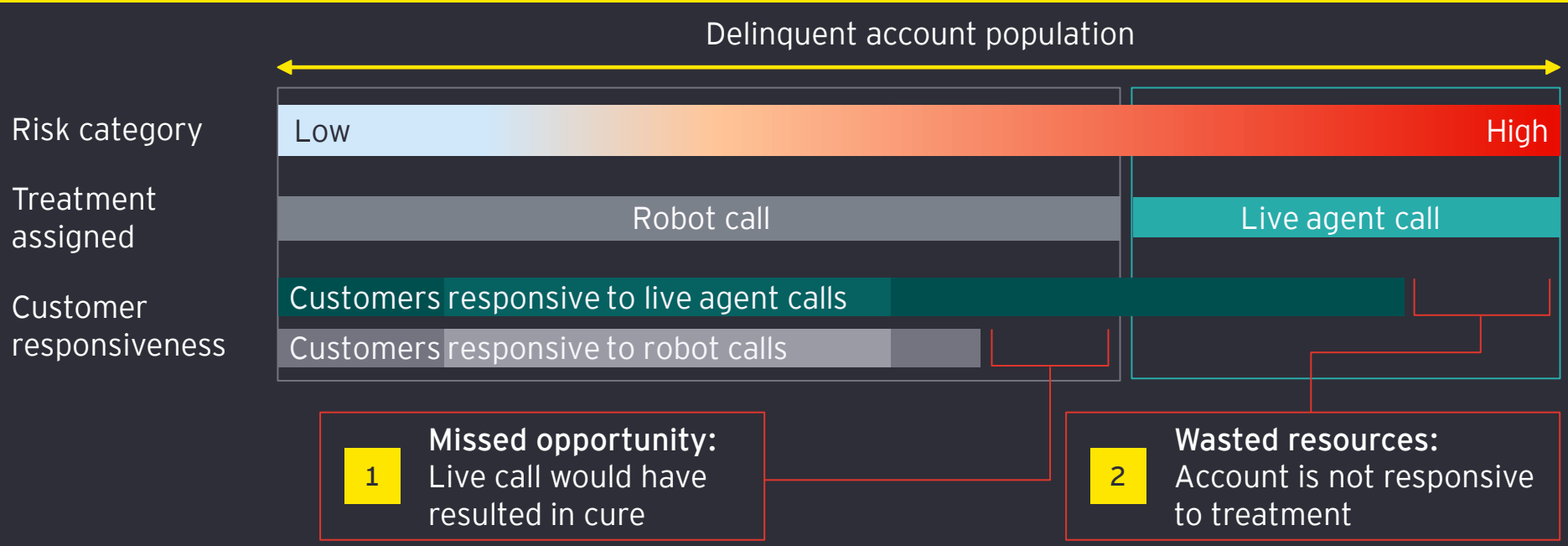


Reinforcement learning can outperform decision trees based on its ability to **handle complex dynamics**, **continuous learning**, **adaptation** and **optimization of sequential decisions.**

Limitations of the current collections approach

Treatment strategy is focused on risk rather than on maximizing treatment impact

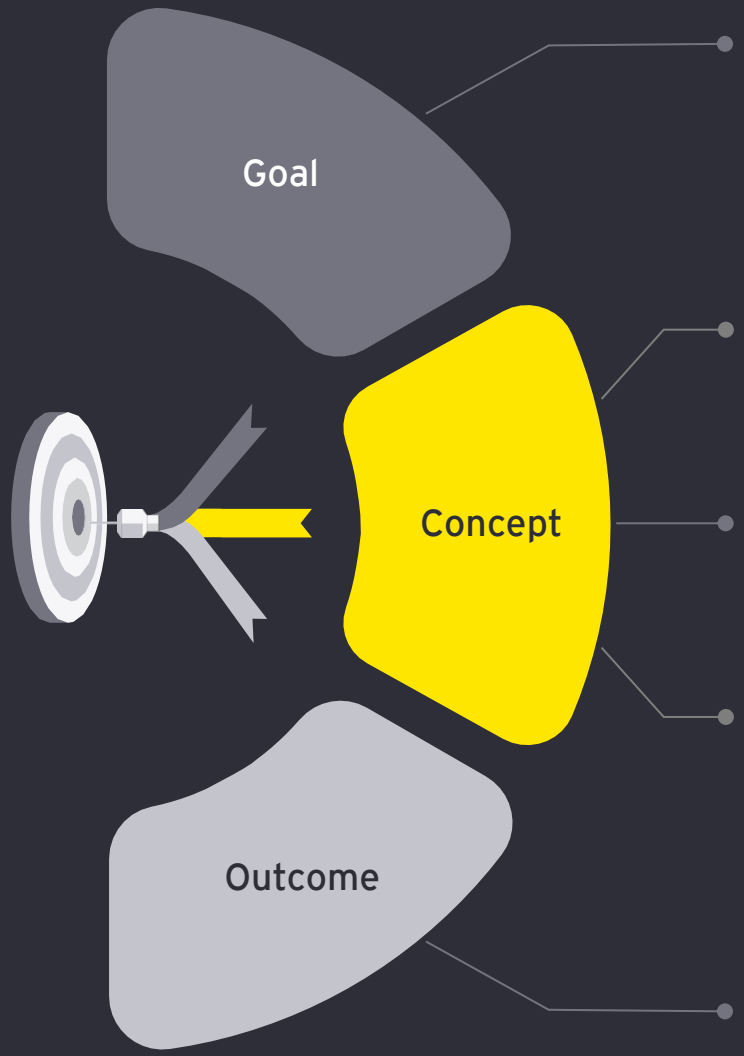
Core limitation: a focus on default risk may not maximize collections effectiveness



Other limitations

- Assigning treatments based on segments puts an upward bound on collections effectiveness. Segments are not homogeneous in how they respond to treatment or change over time.
- No feedback mechanism ties treatments to results. As a result, lessons learned are not applied, creating vulnerability to changes in customer behaviours, macroeconomic fundamentals, and business cycles

How can RL solve this limitation for collections?



Assign collection actions that will maximize repayment and, when possible, eventually lead to account cure.

A series of decisions

- Model each customer's journey through the collections process as a series of "states".
- Each "state" is a snapshot of the customer at a point in time.
- The RL agent makes a series of decisions based on the evolution of states with decisions.

Complex and dynamic environment

- A reward to each action taken is captured in the form of repayment amount and a change in the customer state.
- Customer responses to previous treatments are used to tailor future treatment strategy.

Reward-driven learning

- Maximize both repayments and the long-term outcome or cure.
- Account for decisions resources constraints such as people constraints and costs.

8% reduction in charge-off/write-off

Insights on collections in this large financial institution

Based on the analysis of multi-year collections treatment data across product categories:

1 Certain customers are more susceptible to live-agent calls

- Difference between a live-agent and a robot call is negligible for many high-risk customers.
- Live call has a substantial impact on repayment (vs. robot call) for certain customers in the medium-risk segment.

2 Live-agent calling delinquent customers early leads to large gains

- Early identification and treatment of medium-risk accounts is critical.
- Behavioural data can be used to identify medium and low-risk customers that are likely to remain delinquent.

3 A segment of "uncollectible" will default regardless of treatment

- Often this bucket of high-risk accounts doesn't have the ability to make repayments.
- Strategy should focus on collecting from these accounts early and diverting resources away from these customers when it is unlikely to have an impact on repayment.

Reinforcement learning technology trends

RL technology trends

Technology integration and development

- Integration of RL with natural language processing and computer vision, will further promote automation and intelligence.
- Integration of RL with Quantum computing will enhance computational speed and complex problem-solving.
- Integration of RL with blockchain technology can provide transparent and verifiable environment during the decision making process.

Industry applications extension

- Credit scoring and risk management: Combine RL and machine learning models to more accurately assess credit risks and dynamically adjust credit scoring standards through continuous learning and adaptation to market changes.
- Quantitative Trading Strategies: Use RL combined with deep learning technology to develop algorithmic trading systems that can capture complex market patterns and automatically adjust strategies to improve trading efficiency and profitability.
- Market trend analysis and prediction: RL can use big data analysis tools to conduct in-depth analysis of large-scale market data, learn and predict market trends, and provide support for investment decisions.

How we can help

- **Advanced decision-making services:** EY teams can integrate RL to help optimize decision-making processes, providing you with advanced algorithms that enhance efficiency and outcomes, especially in sectors like financial services.
- **Customized implementations:** EY teams can tailor RL services to your specific needs, integrating them into your existing systems and processes, particularly for automated trading and risk management

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