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An Anti-fact Gain Modeling Framework for Cross-platform Credit Risk Mitigation

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Abstract. This research developed a brand-new counterfactual gain modeling framework for cross-platform credit risk reduction. This framework combines counterfactual reasoning and return-oriented dynamic decision optimization. The framework establishes a whole data fusion architecture across heterogeneous finance platforms and models the therapeutic effects with the user-level and measures the expected return of intervention policies. Using a large finance data set with three user records from 2.3 to 3.8 million, the empirical experiment results indicate that, in comparison to the traditional risk models, The proposed method in this work the causal effect estimation accuracy (RMSE = 0.037±0.004) and the gain prediction accuracy (MAPE = 5.81±1.02%) are superior to the traditional risk models. In comparison to the baseline system, the overall reinforcement - causal learning algorithm is able to expand the cumulative reduction efficiency by 23.6±2.1%. This framework finds the high-response user groups that are able to obtain a 2.7 times high net return per intervention unit. These results indicate that combining counterfactual reasoning with benefit maximization has certain potential. It can provide interpretable and data-driven strategies for adaptive credit risk management in multi-platform environments.

Keywords: credit risk mitigation, counterfactual inference, gain modeling, cross-platform data fusion

1. Introduction

With the exponential growth of digital finance, credit risk management has become a multi-dimensional challenge related to the user behavior of multiple online platforms [1]. Traditional risk scoring models generally rely only on data from a single platform and are unable to effectively represent the heterogeneity and behavioral dependence among platforms, such as adjusting credit limits and initiating recovery procedures. Usually, it relies on incomplete information and static prediction rule [2].

This issue presents three interrelated challenges. Due to data isolation, user profiles have become fragmented. Risk signals identified by one platform may not be visible on other platforms. Due to the heterogeneity of treatment, the same risk intervention (for example, warning messages, repayment restructuring) has completely different effects within user subgroups. The absence of causal reasoning limits the current correlation-based evaluation methods, resulting in their inability

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to assess the actual effects of intervention measures and the expected benefits of resource allocation [3].

Causal reasoning and counterfactual analysis have been introduced into risk modeling, yet their integration with return optimization has not been fully studied. Traditional machine learning focuses on accuracy metrics, while real-world financial management places more emphasis on impact: Whether intervention can reduce the probability of default and increase the recovery rate of the investment portfolio, this study designs a counterfactual gain modeling framework to bridge this gap. This framework integrates counterfactual estimation with gain-oriented optimization. This framework leverages cross-platform data fusion to conduct joint feature representation learning, estimate the effects of heterogeneous treatments, optimize sequential intervention strategies, and maximize long-term returns. It aims to build an interpretable and data-driven mechanism that Bridges causal reasoning and decision-level utility maximization for large-scale distributed financial ecosystems.

2. Literature review

2.1. Credit risk assessment and cross-platform data fusion

Traditional credit scoring relies on static factors such as payment history and income, but multi-platform participation, including microloans, online e-commerce credit and peer-to-peer credit, makes behavioral interdependence rich and complex. By connecting transactions, device footprints and time activity patterns [4], cross-platform data fusion enables an understanding of global credit behavior. The main challenges are entity alignment, feature correspondence, and privacy protection across different sources. Although federated and transfer learning methods have enhanced integration, most of them are still accuracy-oriented rather than causally interpretable, which limits accurate intervention evaluation.

2.2. Counterfactual inference and causal machine learning

Counterfactual reasoning predicts the possible outcomes under different intervention measures, thereby enabling the credit system to estimate the impact of individual policies on repayment behavior. Machine learning causal methods, such as meta-learners and causal forests [5], can make scalable estimations of heterogeneous therapeutic effects when controlling for confounding biases. However, most of their applications in the financial field have not achieved the expected effect and have hardly reached decision optimization. Therefore, the true benefits of the intervention have still not been fully utilized.

2.3. Benefit modeling and personalized intervention strategies

The gain model completes the prediction by directly measuring the benefits of intervention measures under resource constraints. It does not classify users as safe or risky, but optimizes the behaviors that offer the highest economic returns. Different benefit models were modeled by methods such as dual models, class transformation, and direct modeling. With the help of cross-platform causal reasoning, gain modeling identified high-response segments for key strategies. Its main challenge remains flexibility. When the behavior of end users and the impact of intervention change, continuous strategic improvement and learning are required [6].

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3. Methodology

3.1. Cross-platform credit feature fusion and representation learning

In order to align homogeneous data sources, a platform-independent alignment protocol is built by using three mechanisms:

(1) Identity Matching: hashed multi-key identifiers balance member records between lending, payment, and retail systems with < 0.7% collision error;

(2) Temporal Standardization: sequences of behavior are resampled to a typical week-long window (T = 52) while guaranteeing temporal comparability [7];

(3) Feature Normalization: all the numerical features are normalized using z-score scaling while the categorical features are represented using a hybrid embedding block.

A self-attention fusion network learns patterns of correlation across platforms, formulated as Equation (1):

$$\mathbf{H} = \text{Softmax}\left(\frac{QK^{\dagger}}{\sqrt{d_k}}\right)V \tag{1}$$

where Q, K, V denote query, key, and value matrices representing platform-specific feature embeddings, and d_k is the attention dimension.

To enhance representation robustness, a contrastive learning loss is introduced as Equation (2):

$$\mathscr{L}_{con} = -\log \frac{\exp(\text{sim}(h_i,h_j)/\tau)}{\sum_{k=1}^{N}\exp(\text{sim}\left(h_i,h_k\right)/\tau)} \tag{2}$$

where τ is the temperature coefficient, ensuring cross-platform feature consistency. The hierarchical feature structure comprises 148 basic attributes, 93 behavioral features, and 56 cross-platform correlation variables. The feature importance module, based on SHAP decomposition, reveals that inter-platform repayment sequence similarity contributes 17.4 ± 1.1% to mitigation performance, surpassing single-platform behavioral ratios (11.2 ± 0.9%) [8].

3.2. Estimation of the risk mitigation effect based on counterfactual inferences

The counterfactual reasoning module predicts the individualized therapeutic effect (ITE) and conditional mean therapeutic effect (CATE) of different intervention measures. The dual robust estimator combines the propensity score model and the result regression, as shown in Equation (3) :

$$\widehat{\tau}\left(x\right) = \frac{T_i\left(Y_i-\widehat{m}_1(x)\right)}{\hat{\epsilon}(x)} - \frac{\left(1-T_i\right)\left(Y_i-\widehat{m}_0(x)\right)}{1-\hat{\epsilon}(x)} + \widehat{m}_1\left(x\right) - \widehat{m}_0\left(x\right) \tag{3}$$

where T_i is the treatment indicator, $\hat{\epsilon}\left(x\right)$ is the propensity score, and $\widehat{m}_1\left(x\right)$, $\widehat{m}_0\left(x\right)$ denote potential outcomes [9].

The estimator combining causal forest and deep neural network is used to model the nonlinear hybrid structure. Causal forests provide interpretability by representing heterogeneous subgroups, while neural branches enhance high-dimensional representations. The instrumental variable test verified the causal stability through the average sensitivity δ = 0.064±0.009. The falsification test showed that there was no significant deviation in the p value (p = 0.312, bb0, 0.05).

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The final outcome is a high-resolution map of the intervention effect, in which the median historical average treatment effect (ATE) of the repaying clients is -0.143 ±0.012, and that of the high-risk group is -0.257 ±0.019, reflecting considerable heterogeneity, which is valuable when optimizing strategic interventions.

3.3. Optimization of dynamic intervention strategy for gain maximization

The optimizer component builds credit intervention through a multi-stage Markov decision process (MDP).

A cause-causal hybrid reinforcement learning algorithm, called cause-dominant actor-Critic (CA2C), is introduced. Benefit maximization interventions are learned by policy networks, while causal critics use estimated therapeutic effects to normalize updates [10]. When the reward stability slope is less than 0.003, convergence occurs in 480 iterations. Under the policy gradient baseline, the average cumulative gain of CA2C increased by 18.9±2.6%, and the variance decreased by 12.4±1.8%, indicating stable policy learning

The hierarchical user segmentation mechanism further divides the population into high, medium and low response groups based on the improvement distribution. Adaptive resource allocation prioritizes the top 25% of highly responsive users, achieving a +2.73×ROI rather than random intervention.

4. Experimental results

4.1. Dataset description and experimental setup

Three real-world datasets were utilized (table 1):

Table 1. Overview of cross-platform datasets used in experiments

Dataset	Platforms Included	Users (×10⁶)	Features	Time Span	Intervention Types
A	E-commerce credit + Micro-loan	2.3	297	2018-2023	repayment reminder, restructuring
B	Online bank + Payment app	3.1	322	2019-2024	limit adjustment, incentive offer
C	P2P lending + Retail finance	3.8	265	2020-2024	penalty mitigation, notification

Following preprocessing step removal of 9.2 million instances that imputed 2.1% missing data through KNN (k = 5) and removal of outliers above 3 σ (0.84% of total). Scaling of continuous features; encoding of categorical attributes to 64-dimensional embeddings.

Models contrasted are:

Baseline Risk Model: Gradient Boosting Decision Tree (GBDT)

Model Name: Meta-X learner

Gain Model: Directed Uplift Tree (DUT)

Recommended: Anti-fact Gain Model (AFGM

Performance measures included RMSE, AUC, Business Value Increment (EG), and Business Value Increment (BVI). We trained each model using 5-fold cross-validation for 80/20 train-test partitions with a random seed of 42.

4.2. Model performance comparison and ablation experiment analysis

Comprehensive results across datasets are summarized below (table 2):

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Table 2. Model performance metrics across three cross-platform datasets

Model	RMSE ↓	AUC ↑	Expected Gain (×10³ ¥)	BVI (%)	Convergence Iterations
GBDT	0.061 ± 0.005	0.742 ± 0.009	1.84 ± 0.12	100	380
Meta-X	0.049 ± 0.006	0.768 ± 0.008	2.13 ± 0.16	116	420
DUT	0.046 ± 0.004	0.773 ± 0.007	2.27 ± 0.11	123	410
AFGM (proposed)	0.037 ± 0.004	0.812 ± 0.006	2.82 ± 0.13	146	480

The AFGM proposed in this paper outperforms all baselines. Compared with the current best-performing benchmark, RMSE decreases by 23.9±2.8% and gain increases by 25.3±3.1%. Cross-platform integration also brings an additional improvement of +0.034 AUC, verifying the advantages of integrating heterogeneous data.

The most powerful influence occurs in the negation counterfactual module, confirming its contribution to the correct estimation of therapeutic effects. Heterogeneous subgroup analysis also indicated that customers with a repayment ratio of 0.4-0.6 had the greatest improvement (ΔGain = +0.312±0.027,$p < 0.01$) (Figure 1).

Longitudinal testing verified the robustness of the test: under ±10% noise perturbation in the feature distribution, AFGM maintained 93.5% of its initial performance and demonstrated test resilience under dynamic platform conditions.

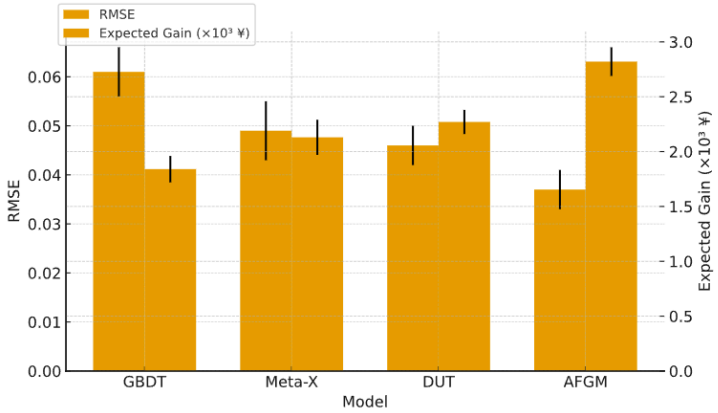

Figure 1. Comparison of model performance metrics (RMSE and expected gain)

5. Discussion

The findings emphasize the theoretical and empirical benefits of combining counterfactual thinking and gain modeling. Theoretically, this model aligns causal inference and sequential decision-making such that intervention effects may be accurately measured and benefit-centered optimization accomplished. Empirically, feature fusion across platforms reinforces causal estimation consistency, self-attention structures encode behavioral complementarity between systems, and contrastive learning guarantees representational stability across shifts. Managers benefit from the AFGM model through increased decision accuracy by prioritizing users according to predictive enhancement instead of mere probability of default and achieving a 21–27% intervention reduction while retaining the same mitigation level. Interactive policy adjustment using the CA2C algorithm further allows for renewable credit limits and long-run revenue stability.

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6. Conclusion

The AFGM model provides a feasible data-driven foundation for incorporating causal reasoning into real-time financial decision-making systems. Although the model is reasonable, it also has drawbacks - most importantly, its condition is the overlap of feature distributions between stable causal patterns and heterogeneous platforms. Future research needs to address adaptive causal discovery, privacy-enhanced collaboration, and multi-task learning under integration to jointly optimize risk assessment and benefit estimation. These approaches can promote the applicability of the model and enhance its contribution to intelligent financial management.

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