Accurate Credit Scoring for Blockchain Lending with Conformalized Quantile Regression

Abstract—**Lending is a fundamental financial activity that traditionally relies on the estimation of the risk of borrowers failing to repay loans. Decentralized Finance (DeFi) lending services have an inherent challenge following the anonymity of users, making it challenging to estimate the risk of a particular borrower. Accordingly, blockchain loans are based on either the immediate return of the loan or more commonly on collateral that serves as a guarantee for the repayment. Even with such collaterals, risk estimation is crucial to guarantee the ongoing operation and revenueability of the lending protocols, allowing them to be selective in providing loans and setting interest rates. This work describes a risk estimation of high accuracy for borrowers based on their past activity. To achieve this high accuracy we suggest to rely on a method known as conformalized quantile regression that can apply to a wide range of estimation methods. We show the effectiveness of the approach based on a large dataset of real loan activities from Compound V2, a major DeFi lending protocol.**

I. Introduction

Decentralized Finance (DeFi) represents an emerging technological paradigm in the realm of a wide range of financial services through smart contracts over blockchain networks. Among others such services include decentralized exchanges (DEXs) facilitating the trading of cryptocurrencies, insurance services and lending protocols [1]–[4]. As of late 2021, the estimated DeFi market size was over 180 billion US, and by December 2022 was evaluated as of 39.6 billion USD.

Lending is among the most important financial activities, coming in various forms, such as government bonds, corporate debt, mortgages, student loans, and consumer loans. DeFi loans have emerged in recent years with the appearance of loan decentralized protocols such as Aave, Compound, Cream finance, and MakerDao [3], [5], [6]. DeFi lending services encompass two distinct loan types, primarily differentiated by their respective timeframes.

The first type is known as *flash loan*, wherein a borrower acquires and repays a specified value within a single transaction, typically without requiring collateral as security. This form of loan is constrained by a brief time window and is frequently utilized for capitalizing on arbitrage opportunities in decentralized exchanges (DEXs) [7], [8]. In contrast, the second type of loan is referred to as a *collateralized loan*. This category allows for long repayment periods (e.g., weeks or months) and generally incorporates interest rates determined based on the loan duration and involved risk [5], [9].

Similar to traditional loans, an inherent risk is involved in DeFi loans. In DeFi collateralized loan, collateral plays a crucial role in mitigating this risk, serving as a safeguard in case the borrower is unable or unwilling to fulfill their loan repayment obligation. In DeFi lending services, the loan is often given in stablecoins, whose values tightly follow the USD. Collateral is given in cryptocurrencies of large market cap, like ETH, the native coin of the Ethereum network, as well as in other cryptocurrencies of smaller market cap.

In addition to the regular risk inherent in the ability of borrowers to repay loans, DeFi lending has another source of risk, namely, the volatility of cryptocurrencies. This additional risk is mitigated by the requirement for over-collateralization - a requirement that the value of the collateral is higher than the loan value. As the ratio of collateral to loan value changes constantly, based on market prices, to avoid under-collateralization, lending protocols often define minimal thresholds (with typical values of 120-300%) for various cryptocurrencies, such that when the collateral to loan ratio falls below the threshold, the loan is liquidated and the collateral is sold. This eliminates the need to return the loan. To reduce the chances of the collateral becoming liquidated, in practice, a borrower often provides collateral of even higher ratios.

Credit scoring was studied even earlier than the appearance of the blockchain technology with the development of many classification models [10], [11]. It often refers to indications on borrowers based on historical debts and other characteristics that should shed light on their ability to return a potential loan. Lenders (such as banks) use credit scores to determine who qualifies for a loan, what should be the interest rate and other loan conditions. Machine learning algorithms are often used, but the baseline model is typically a logistic or probit model, as they are simple to implement and interpret [12]–[14]. Credit scoring on blockchain protocols has advantages over traditional banking platforms, including timeliness and accuracy of loan-related data.

The accuracy of credit scores is of high importance. For instance for a bank, underestimation of the risk may result in many loans given to borrowers with challenges to repay them. On the other hand, overestimation of the risk can reduce the gains of the bank duo to not providing loans to borrowers that could have paid them back. Beyond a single numerical value, a credit score can be associated with an interval of values, indicating that the correct score should be within the range with a probability of at least some tunable confidence level p. The higher the confidence level, the larger the interval needs to be.

Deriving short intervals on the risk for some minimal confidence level is useful for a bank to operate safely and achieve revenue. For instance, a bank can take a conservative approach and refer to the lower bound of the range of risk values or alternatively focus on the value in the middle of the intervals. This paper suggests to rely on a recent method by Romano et al. named Conformalized Quantile Regression (CQR) [15] to derive short intervals on the risk estimation. While we demonstrate the effectiveness of CQR on a particular estimation method of the credit scoring, we explain that the approach is general and can be applied for a wide range of estimation methods.

We focus on long-term loans (rather than flash loans) to assess the risk of a user defaulting, to allow for better decision-making before approving the loan. As flash loans are already accessible without the need for high funds, our study does not focus on them.

Contributions and paper overview. In Section II we overview the basic mechanism of DeFi lending protocols and present the terminology of the paper. Next, we refer to the Compound lending protocol in Section III. We describe the type of its available data and analyze basic statistics. Next, in Section IV we overview the conformalized quantile regression (CQR) method and explain how it can be applied to derive credit scoring of high accuracy toward an informative decision model for lending protocols. We conduct experiments to evaluate the effectiveness of the proposed method in Section V based on real lending transactions from the Compound lending. Finally, conclusions and directions for future work can be found in Section VI.

II. Background on DeFi Lending

Glossary. We overview basic terminology related to blockchain-based loans.

lending protocol: A smart contract allowing interaction of the various actors to supply collateral, take loans, or deposit liquidity.

stablecoin: A coin whose value aims to be pegged to a fiat currency, often the US dollar, like USDC.

loan: A loan is an amount of money borrowed and has to be paid back, usually together with an extra amount of money called interest. Lending in the blockchain world concerns the lending of cryptocurrencies (it may be one or multiple) and is enabled by smart contracts.

liquidity provider: An entity providing liquidity to the protocol in exchange for an interest rate. A lender does not interact with a particular borrower.

borrower: The entity receiving the loan in return for interest.

collateral: In collateral-based loans, a collateral is a guarantee provided by the borrower, usually in cryptocurrency. It is returned to the borrower upon returning the loan (with its interest).

liquidator: In collateral-based loans, a liquidator is a user who buys a collateral (often at a discount relative to current market prices), when a loan becomes eligible for liquidation.

Common Lending Protocols Scenarios. A loan with collateral works as follows. A user first supplies collateral to the protocol in the form of a cryptocurrency among those supported by the protocol. The user can then ask for a loan of some value. When a loan is provided, the collateral is locked until the debt (including interest) is repaid. The protocol defines a liquidation threshold for each type of collateral (a particular cryptocurrency). Such a threshold indicates a lower bound on the ratio between the collateral value and the loan value. The threshold can vary among cryptocurrencies, e.g., based on their volatility or on the ability to exchange them. While satisfying the lower bound, setting the exact ratio with some collateral value is due to the choice of the user. When the value of the collateral drops and the ratio falls below the threshold, the collateral is sold by the protocol instead of repayment of the loan.

A collateral of value higher than the loan amount is required for several reasons. First, it aims to motivate the borrower to return the loan. Second, it deals with the risk of high volatility in the value of the collateral. Because of network congestion between the decision and the liquidation process by the network, there might be a delay (as for every transaction). During that time, the value of the collateral may drop even further. Overall, this type of loan can end in one of two possible ways:

Case 1: The borrower repays the loan fully with interest. The collateral is unlocked and is returned to the borrower.

Case 2: The ratio of collateral to loan value drops below the threshold and the loan is liquidated, upon one of the following scenarios

- The collateral provided decreases in USD value
- Interest accrues over time, increasing the debt value

A combination of those scenarios is also possible. When the ratio falls below the threshold, the protocol allows the liquidation of the account. A liquidator repays the debt and receives the collateral of the borrower, and the loan is terminated.

Example. Consider two users borrowing a loan of amount X. They provide the same type of collateral for which the liquidation threshold is 130%. Namely, if the value of the collateral falls below 130% the value of the loan, the collateral is automatically liquidated by the protocol. User A provides a collateral of value 2.5X and user B provides one of value 3X. Suddenly, a price change causes the collateral to lose half its value. The loan of User A is liquidated, as it has passed under the 130% liquidation threshold. On the other hand, the loan of user 2 is not liquidated as its ratio was at least 150% of the loan. Note that user 1 could have prevented liquidation by providing further collateral.

III. Dataset from the Compound V2 Protocol

A. Methodology and Transaction types

Towards proposing the approach and evaluating it, we overview the Compound lending protocol [16], established early in 2019. As of 2023, Compound has a total value locked (TVL) of about 2.2B USD.

To carry out our study, we collected the transactions across all the different contracts of Compound V2 (the transactions of the CToken contracts and the transactions of the comptroller). We then used the different events to build a user profile. We look at each transaction and all the users that are mentioned

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as borrowers in a small list of relevant events that are emitted from each one of the smart contracts to reflect the different actions taken by borrowers as mentioned in Section II. This helps us build the statistics for each borrower account.

The analyzed events are the following:

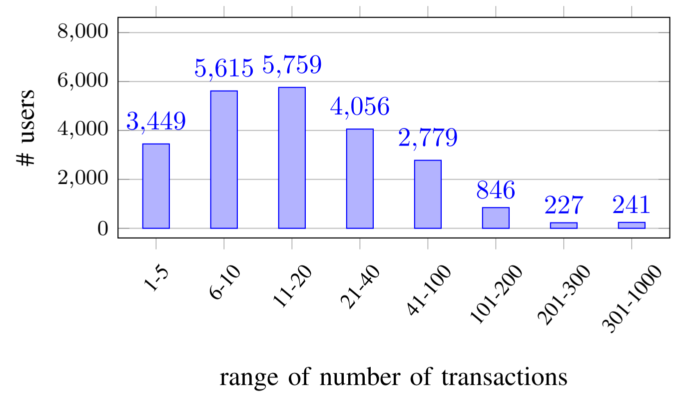
- Borrow: whenever a user borrows one of the assets. The field named ”account borrows” contains the total amount currently borrowed including interest, the field named ”borrowAmount” indicates the amount of the current loan and another field mentions the asset borrowed.
- RepayBorrow (Reimbursement): In a mirror way to borrow, this event mentions the amount paid and the leftover debt of the account (0 in case of full repayment). The payment can be made by any account not just the user’s.
- Mint (Collateral Supply): By providing coins to the collateral in one of the accepted assets a user is able to mint the equivalent in CTokens (Compound Tokens).
- MarketEntered: To use liquidity that was given (in a mint event) as collateral, a user simply asks the protocol to consider his coins in a specified asset as collateral. Registering the coins as collateral allows the user to borrow from the protocol having the collateral as a guarantee.
- Redeem (Collateral Withdrawal): This event represents the burning of CTokens to gain back the base asset that the user gave the protocol. This is not possible if the coins in the base asset serve as collateral for an open borrow.
- MarketExited: The user asks that its value in some asset would not serve as collateral anymore. The event is impossible if the coins currently serve as collateral for an existing loan.
- LiquidateBorrow (Liquidation): The borrower’s loan is paid back by another user (i.e. liquidator). This liquidator can then claim the borrower’s collateral.

B. Lending Protocol Statistics

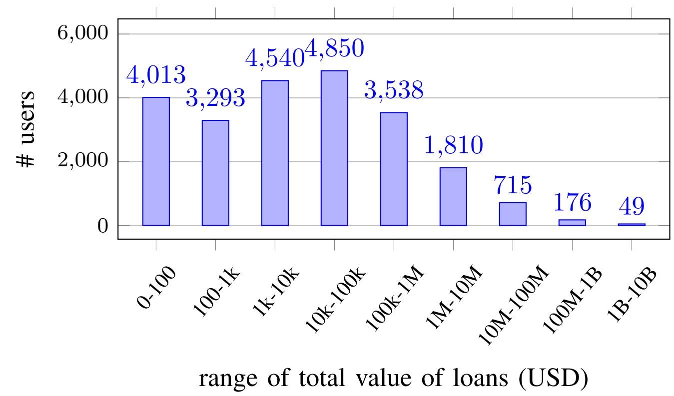
We collected information from one of the biggest lenders, Compound Version 2. The data dates from May 2019 up to May 2023 approximately four years of data. There are 22994 different borrowers. Among them, 549 borrowers (2.39%) were liquidated at least once. The number of liquidations is 1756 with 353 borrowers being liquidated more than once. The number of liquidation events is small (0.88%) with respect to the total amount of loans (199400). Note that a liquidation event does not refer to particular loans but to a borrower with its aggregated total updated debt. Table I presents the

Transaction (event) type	Number	Value (USD)
Borrow	199400	64B
RepayBorrow (Reimbursements)	124397	60B
Mint (Collateral Supply)	93188	36B
LiquidateBorrow (Liquidation)	1756	NA

Table I: Distribution of lending events in Compound V2 (May 2019 - May 2023)



(a) Number of transactions per user



(b) Aggregated values of loans per user

Figure 1: Compound V2 data analysis - Distribution of the number of transactions and total values of loans per user

transaction types and their importance in the model. The vast majority of the events refer to borrowing and reimbursements.

Similarly, Figures 1a-1b represent the value loaned by users and the number of transactions each performed. Most accounts have a relatively small borrow and total number of transactions making a prediction tougher because past data is relatively small.

IV. Applying Conformalized Quantile Regression for Accurate Decision Model

A. Conformalized Quantile Regression (CQR)

Conformal prediction is a general methodology for providing prediction intervals, namely ranges of values with coverage guarantees [17], [18]. It is based on fitting a regression model on a training set of samples which is followed by quantifying its certainty with a validation set. In such traditional methods, it is difficult to develop intervals of variable length for particular estimations, making these intervals to be often conservative. Conformalized quantile regression (CQR) was introduced by Romano et al. in 2019 [15]. The technique is derived by mixing conformal prediction with quantile regression and can enhance any algorithm for quantile regression, including random forests and deep neural networks. It computes intervals

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of short average length that are adaptive to heteroscedasticity and achieve high statistical efficiency with high coverage rate.

B. Quantile network and CQR Quantile network

A quantile neural network is a neural network architecture made for quantile regression, allowing it to predict various quantiles of a target variable's distribution. Quantile regression is a statistical technique used in machine learning and statistics to model and predict different quantiles of a target variable's distribution, as opposed to just predicting the mean.

In a quantile neural network, the network architecture is adapted to predict specific quantiles of the target variable's distribution. This is achieved by having multiple output nodes in the neural network, each corresponding to a different quantile. For example, in our model, we want to predict the 5th, and 95th percentiles of a distribution so there are two output nodes in the network, each producing a separate prediction. Quantile neural networks help to understand the uncertainty or variability in predictions. CQR quantile network is a Quantile network wrapped by the framework of [15].

C. User's generated revenue and paremeters

We created a score for each user which reflects the revenue the user brings to the protocol. How much does the protocol receive for the user's total borrows? Any user with a negative score should be rejected as it causes loss and any user with a positive score should be accepted.

These features are a range of characteristics computed on a daily basis. For each day, the amount of debt and collateral in USD is given, any liquidation event, and the balance of each of the coins for each of the supported tokens. The last day of data gathering is May 28 2023. Therefore features are computed until three months before this date to show the model's ability to predict the future revenue based on past data.

V. Experimental Evaluation based on Real Lending Data

We use real data of 200 users of the Compound Version 2 lending platform from May 2019 up to May 2023 to evaluate three models. The models are:

1) Approve All
2) Quantile network
3) CQR quantile network

The estimation is for the revenue a potential loan to a certain borrower would yield the platform. We use the intervals generated to decide if the protocol should grant loans to a the borrower. Each positive number indicates the user will enable the protocol to generate (positive) revenue, and, consequently, the protocol should approve the loan. The theoretical revenue of the protocol is computed under three decision models.

Model 1: Every loan is approved and the total payments minus the total loans of all users is the revenue.

Models 2-3: Loan of a user are approved if the medium value of the intervals created using quantile network or CQR quantile network yields a positive result. For approved users, the total payments minus total loans is the revenue.

Model	Average interval length (USD)	Loan approval rate	Interval coverage	Total revenue
Approve all	NR	100%	NR	-4.67B
Quantile network	76357.98	14.5%	89%	-0.98B
CQR quantile network	37539.06	8.5%	89%	-2.3M

Table II: Revenue for various models for Compound V2

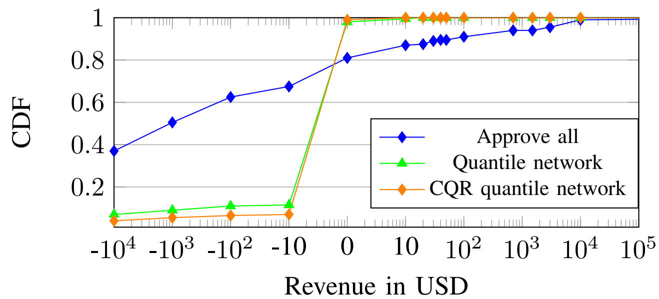

Figure 2: Revenue generated using approval techniques

Note that as many loans are active, the revenue is often negative. To mitigate this fact, we only took into account loans that were taken at least three months before the last day recorded from Compound giving enough time to pay back. A loan on such a protocol is not limited in time.

Overview of the results is presented in Table II. The table indicates the average interval length, to the ratio of approved loans, to the rate of the revenue was included in the estimated interval (coverage) and to the total revenue. By being selective and approving only part of the loans, Quanitle network and CQR quantile reduce the loss. CQR helps create a smaller interval without sacrificing coverage. Coverage helps to obtain a good estimate of the user's risk and can prevent defaults. Overall, CQR quantile reduces the negative revenue by 99.95% of approve all and by 99.76% of the Quantile network.

Fig. 2 presents the Cumulative distribution function (CDF) of the revenue over all users for each model. Users without an approved loan imply revenue of 0. By estimating the revenue in high accuracy, Quantile and CQR help to reject many of the loans with a negative revenue. In particular, the ability of Quantile CQR to identify loans of significant negative revenue and avoid them allows its significant savings. For instance, CQR helps to bound the ratio of loans with a loss of 1000 USD or more to at most 5.5% of the loans in comparison with 9% and 50.5% in Quantile network and approve all, respectively.

VI. Conclusions and Future Directions

We presented an early promising approach to credit scoring that leverages the strength of CQR to provide estimations of high accuracy. It allows for increasing the revenue of lending protocols by better-identifying borrowers who have a high chance of not repaying loans. This enhancement can be applied to various estimation methods of the risk of borrowers and allows small intervals for such estimations. Future research would enlarge the evaluation for additional lending protocols and would examine its effectiveness to enhance additional estimation methods.

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