Machine intelligence for housing finance

Abstract
Despite its trillion-dollar market size, housing finance technology is still predominantly outdated, relying on manual paperwork and grid-based decisions. Massive amounts of data and deep learning technology enable promising advances in the field. Giesecke and team have developed a deep learning model of mortgage credit and prepayment risk that is able to capture nonlinear relationships, thereby outperforming previous empirical models. They also analyzed influential risk factors and developed statistical significance tests for neural network models' explainability.

Main
Housing is a major problem for Americans, with 10 million mortgage applications processed annually and single-family mortgage debt outstanding at $10 trillion. The mortgage security market is greater than $10 trillion, while the value of U.S. housing stock is greater than $20 trillion. Despite the enormous market size, housing finance is still using 20th century technology. Manual, paper-based applications make the process slow and costly. Grid-based underwriting leads to sub-optimal decisions, such as rejecting good risks or approving bad ones.

With 21st century technological advances, fintech startups like Blend and Roostify are building products that aim to improve the home loan experience. Machine intelligence can replace the grid with automation in various processes (e.g., underwriting, pricing, insurance, etc.) and enable housing security markets to become more transparent and efficient. These technologies have to the potential to expand access to mortgage credit, reduce the risk of financial crises, improve capital allocation, all of which could generate significant benefits to the society.

One key to unlock machine intelligence in housing finance is data. For example, we can use data to understand borrower behavior in different stages, e.g., loan and pool level risk during post-origination, hedging during applications, collateral valuation during underwriting. Fortunately, the amount of data in housing finance is massive. Existing ones include monthly loan-level performance from 1994 to 2015 (200 million loans), property-level sales transactions from 2000 to 2014 (100 million sales), etc. In the future, there are borrower-level data from bank account transactions, credit history, social media, and property-level images.

Another crucial key is the rise of deep learning. Typical empirical mortgage research usually constrains the relationship between risk factors and mortgage performance to be of a pre-specified form; linear is the standard choice. However, the relationship is not linear, as seen in the time since origination vs. prepayment rate or prepayment incentive vs. prepayment rate plots in class. To capture this non-linearity, Giesecke and team developed a deep learning model of mortgage credit and prepayment risk where the relationship between risk factors and mortgage performance is not assumed to have a pre-specified form. The advantage of deep learning over traditional models also include the ability to exploit all billions of data points available, incorporate large number of factors, and distinguish between multiple loan states.

The study used data licensed from CoreLogic, a financial data analytics company. The data include 120 million prime and subprime mortgages originated across the US between 1995 and 2014. Each sample in the study consists of a monthly performance of each loan, summing up to more than 3.5 billion observations in total. They complement the loan-level with local, regional, and economic factors from BLS, Zillow, etc. that may influence loan performance.

The deep neural network model takes in 272 risk factors and outputs the conditional state transition probabilities. The monthly transition matrix is allowed 7 states for the mortgage: current, 30 days delinquent, 60 days delinquent, 90+ days delinquent, foreclosed, REO, and paid off. It obtains superior out-of-sample predictions of borrower behavior over any future time period. The team also performed analyses on the most influential variables and delinquency rates and explored investment portfolio design.

Mortgage underwriting is heavily regulated, and regulators insist on explainability of underwriting decisions to avoid discrimination and ensure fairness. Since deep learning models typically lack explainability, Giesecke and team have developed statistical significance tests for neural networks in order to discern the impact of individual variables on the model prediction. The gradient-based test statistic can be used to rank variables according to their influence, such as evaluating a risk factor's importance in mortgage performance.

With abundance of data and powerful computational algorithms, machine intelligence is transforming housing finance. The technology can also be applied in other lending areas, including consumer/student/auto loans, credit cards, and SME credit.

References

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