Reinforcement Learning for Household Finance: Designing Optimal Policy for Mortgage Market

Reinforcement Learning

Arka P. Bandyopadhyay
Lilia Maliar

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Motivation

- We focus on household mortgage decisions and optimal policy of the servicer to increase mortgage market efficiency.
- Monitoring borrower behavior in real-time and making informed decisions are extremely challenging and costly.
- Sticks and carrots approach has been undertaken anecdotally. *Carrot* is a reward for payment on time and the *Stick* is a consequence for noncompliance.
- The servicers would prefer to know which borrowers to reach out to (Outbound) and which borrowers to respond to (Inbound $\longrightarrow$ Outbound)
- Co-operative borrowers can be negotiated with vis-a-vis loan-modification and Bankruptcy Chapter 13 can be preempted.

Our Reinforcement Learning Approach

- Profit maximization of the servicer as the objective and characterize the optimal policy of the servicer.

- The servicer can use the quantified soft information (Bandyopadhyay (2020c)) (unstructured text information about borrower untracked after origination) about the borrowers (Bandyopadhyay (2020a)) from their communications (call transcripts) with the borrowers.

- We alleviate the information asymmetry between the borrower and the servicer (Bandyopadhyay (2020b)).

- Reinforcement Learning also learns the noisy borrower type over time, i.e., whether she is optimistic or pessimistic depending on positive or negative view about the future of the housing market and the overall macroeconomy.

- To the best of our knowledge, we are the first to use the state-of-the-art RL techniques to design optimal mortgage-market policy.

Housing and Mortgage Market

- Household mortgage market is highly fragmented and illiquid.
- The first aspect makes this market inefficient nationally but locally efficient because of local microstructure invariance (Kyle (2016)).
- The second aspect renders an extremely high liquidity premium.
- To complicate matters further, there are search frictions during buying and selling of these properties and time lag in the sale from listing to closing a property.
- RL can dynamically evaluate the optimal policy of the servicer by extracting signal from the changes in environment (housing market and political economy) caused by the noisy borrower actions.

Current Qualitative (adhoc) Methodology

- The current methodology is based on a qualitative due diligence process by the servicer.
- Title, Foreclosure, Bankruptcy, Property data ordered, Collateral files and servicing comments are received, processed and proofed.
- Compliance data are extracted from collateral files, Collateral logic trees are run, Title logic trees run, Title Due Diligence tasks created, Legal logic trees run, Legal Due Diligence tasks created, Property Due Diligence tasks created, assigned and completed, Combined Grades determined, exception reports created, seller negotiations occur, Final Loan/Funding schedules created, contracts signed, funding occurs.

Methodical Precision of Curative Processes

- The above scenario can be handled methodically by negotiating with the borrower after accessing their soft information and the pertinent issues can be mitigated making the loan eligible for repooling.

- We find clusters of similar words to our prespecified keywords (chosen from qualitative expert judgement and historical perspective). These similar words can be converted to vectors and can be used to quantify higher-dimensional soft information (beyond positive or negative sentiment).

- To achieve this objective, we first plot the main adverse delinquency states, namely, "delinquent", "bankruptcy", "foreclosure", "reo", "short sale", using T-SNE, which is just a two-dimensional visualization of clusters of similar words, with the axes scaled appropriately to fit important similar words.

Designing Optimal Policy

- We design an optimal policy for the servicer stricter than carrots and more considerate than sticks.
- Although we maximize the profit of the servicer to derive the optimal policy of the servicer, the RL paradigm can extract the best course of action towards the borrower assuming the borrower is an adversary agent (Goodfellow, Pouget-Abadie, Mirza, Xu, Warde-Farley, Ozair, Courville, and Bengio (2014)), whose interest may not be always aligned with that of the servicer or eventually the lender.
- We simulate the "housing market environment" using our proprietary Epsilon data about borrower spending habits, demography, income bracket, real-time unemployment status, etc.
- We benchmark our optimal policy against the current adhoc qualitative methodology used by the servicer. For each loan and for each month, we do have the action (strategy undertaken) by the servicer.
- The clear dollar difference in collections vis-a-vis our optimal policy over extant servicer action will provide direct evidence of our quantitative approach and incorporate feedback loop from the housing market and the macroeconomy.

Data

- We will use a unique dataset including approximately 23,000 loans over a period 09/2017 to 11/2020 for our in-sample and validation phases of the Reinforcement Learning.
- Mortgage delinquency classes include B120D (Beyond 120 days), BK (Bankruptcy), FC (Foreclosure), PIF (Paid-in-Full), REO (Real-Estate owned), ShrtSal (Short Sale), W0 30D (Within 0 to 30 days), W30 60D (Within 30 to 60 days), W60 90D (Within 60 to 90 days), W90 120D (Within 90-120 days).
- To capture the spending patterns, demography, relocation and several other aspects of these borrowers, we will use proprietary data from Epsilon, having the following variables: Ethnic Group Code, Language Code, Household Marital Status, Number of Adults, Length of Residence, Household Age, Presence of Children, Household Size, Household Education, Target Income, Net Worth, Liquid Resources, Investment Resources, Wealth Resources, Short Term Liability, Target Income Indicator, Household Political Party, Other Credit - Financial Services Banking, Move Residence Trigger Date (YYYYMM), Year Home Built (YYYY), Target Narrow Band Income, Buy a House Trigger, Buy a House Rank, Move Residence Trigger, Move Residence Rank, Home Loan Trigger, Home Loan Rank, etc.

Dynamics of Delinquency Status
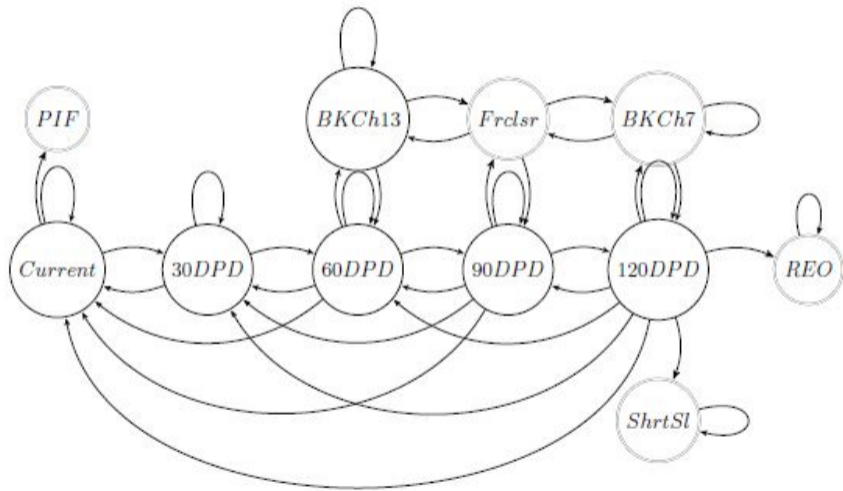
Data

- The disposition strategy (action space) that the servicer chooses to take could be any of the transitions in the figure. The action space consists of but are not limited to: Pending Foreclosure Completion, Pending Claim, Notice of Intent Filed: Not in Foreclosure, Bankruptcy, Not Referred for Short Refinance, Modification in Review, Real Estate Owned, Pending Short Sale, Pending Deed-in-Lieu, Pending Repurchase, Consent Judgment Approved, etc.

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Literature Review

- Christ, Sedatole and Towry (2012) examine the effect of incentive contract framing on agent effort in an incomplete contract setting.
- Dittmann, Maugand Spalt (2007) analyze optimal executive compensation contracts when managers are loss averse which render a convex and increasing optimal contract.
- Corman and Mocan(2002) investigate the effect of economic conditions (carrots) and sanctions (sticks) on murder, assault, robbery, burglary, motor vehicle theft, grand larceny, and rape.
- Bier and Hausken (2011) model distinguishes between the effects of negative incentives ("sticks")and positive incentives ("carrots") for influencing the behavior of intelligent and adaptable adversaries.

Cross-sectional Results and Motivation for RL

I create a time-invariant target at borrower level, namely *Responsiveness*, from the novel data on proprietary servicer call transcripts.

1. *Months of Delinquency*: I assign numeric values to months of delinquency in reverse order, which is in line with increasing responsiveness, *Paid Ahead* := 4, *Current* := 3, *1 month behind* := 2, *2 months behind* := 1 and *3+ months behind* := 0.

2. *Loan Status*: Numeric values to Loan Delinquency Status, with less scores assigned to adverse status: *Current* := 6, *30 days delinquent* := 5, *60 days delinquent* := 4, *90 days delinquent* := 3, *Bankruptcy* := 2, *Foreclosure* := 1 and *120+ days delinquent* := 0.

3. *Known Inbound Calls*: I calculate the sum of all known Inbound communications from inception till date for each borrower.

4. *Inbound calls from borrowers as a return to the servicer Outbound calls*: I create a relative measure of the number of return Inbound calls by the borrower per Outbound call of the servicer.

5. *Information Content*: Reasons for the calls, including Outbound Calls, Inbound Return Calls, Communications regarding Forbearance, Foreclosure moratorium, loan modification, etc., borrower reported unemployment and curtailment of income.

Responsiveness Vs Months of Delinquency

Responsiveness Vs Months_Delinquency

Months of Delinquency
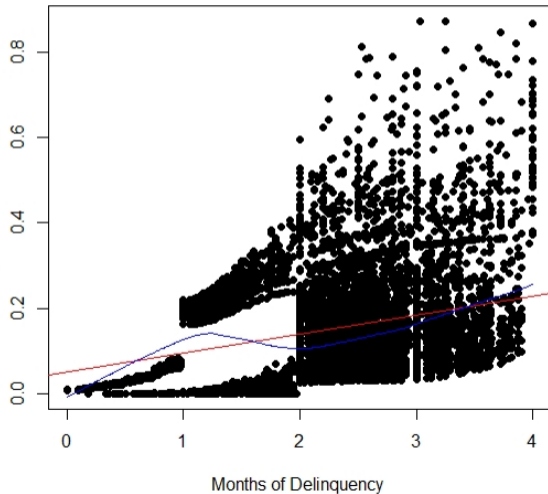
Responsiveness Vs IB_per_OB
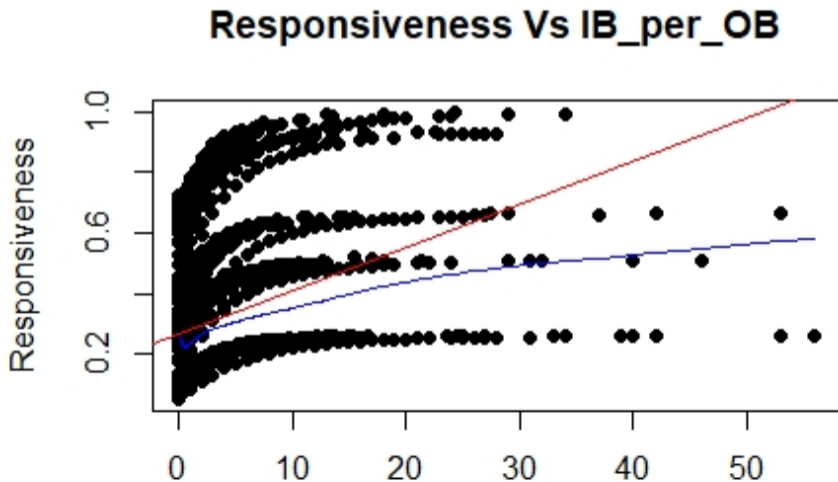
Variable Importance

	variable	relative_importance	scaled_importance	percentage
1	mod_date	1075.59	1.00	0.17
2	original_fico	441.61	0.41	0.07
3	current_rate	439.89	0.41	0.07
4	current_fico	412.80	0.38	0.07
5	orig_ltv	291.95	0.27	0.05
6	original_rate	288.24	0.27	0.05
7	fc_stage	269.14	0.25	0.04
8	Year Home Built (YYYY)	265.78	0.25	0.04
9	Buy a House Rank	257.29	0.24	0.04
10	bk_dq_delay	252.61	0.23	0.04
11	Home Loan Rank	252.50	0.23	0.04
12	Move Residence Rank	228.07	0.21	0.04
13	Move Residence Trigger Date (YYYYMM)	209.98	0.20	0.03
14	Advantage Length of Residence	155.86	0.14	0.03
15	Investment Resources 2.0	147.94	0.14	0.02
16	Short Term Liability 2.0 Code	140.99	0.13	0.02
17	Advantage Household Size (Enhanced)	137.81	0.13	0.02
18	Advantage Household Age (Enhanced)	134.22	0.12	0.02

Conclusion

- Because of information asymmetry at loan-level, the financial intermediary in the mortgage market, namely the servicers have anecdotally used sticks or carrots approach.

- We show that it is possible to measure the responsiveness of borrowers based on our unique administrative data set of text communications between the borrowers and the servicers. We provide evidence that more responsive borrowers co-operate upon communication with them.

- This necessitates a dynamic setting where one can evaluate an optimal strategy for the servicer, which is mostly aligned with the lender (for master servicer) and investor (for special servicer).

- Our paper provides a quantitative framework for servicers to target specific responsive borrowers who have higher propensity to co-operate and hence optimal action by the servicer enables us to document the most efficient transition among delinquency states during the life of a loan.

Please email with feedback/comments at
arkaprava.bandyopadhyay@colorado.edu