Machine Learning in Asset Pricing Chapter 6

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Recap: What have we learned

- ML enables us to confront the high dimensionality problem in asset pricing
- Potentially help our understanding of how assets are priced in theory
- Integrating economic intuition with ML can produce better results than off the shelf ML
- The literature remains in an exploratory phase and there is much that can be done

Empirical Research Agenda

- Characterizing Investment Opportunities (MLAP 6.1)

- Asset Demand Analysis (MLAP 6.2)

MLAP 6.1

- Early work has generally applied off the shelf ML methods
- Future work can apply economic intuition in at least 3 ways
  - Economic Restrictions
  - Nonlinearities
  - Structural Change

MLAP 6.1.1

- Given low S-N ratio, purely data-driven approach unlikely to work
  - One can inject economic restrictions through prior beliefs in a bayesian regression setting
- Open questions:
  - Can one find more economic driven optimization functions for NNs?
  - Economic interpretation of ensemble methods?

6.1.2 Nonlinearities

- Do linear models with interactions (e.g. e-net) outperform nonlinear methods like NN or trees?
  - Kelly paper shows nonlinear outperforms linear wo interactions amongst firm characteristics
- Interpretation is also an issue for nonlinear models
  - Horel & Giesecke (2019) provide a metric to test feature significance in NNs

MLAP 6.1.3 Structural Change

- Current research generally neglects the issue of structural change
  - Assume stable law of motion over long horizons
- ML literature on various updating schemes
- Some considerations
  - Computational intensity
  - Economic intuition

MLAP 6.2 Asset Demand Analysis

- Asset demand via holdings

- Asset demand via investor expectations using analysts forecast

MLAP 6.2.1 Demand Estimation

- Demand comes from observable (firm characteristics) and unobservable characteristics
  - Accurate estimates of the demand system can improve counterfactual exercises (e.g. supply shock effect on asset prices
- This problem suffers from high dimensionality, investor level sparsity, and structural change

MLAP 6.2.2 Expectations Formation

- Beliefs $\longrightarrow$ Demand $\longrightarrow$ eqb prices
- In sample returns driven by forecast error are not predictable in OOS data
- Therefore, OOS testing, as well as structural change can potentially improve understanding of expectation formation

6.3 Theory Applications

- Bounded Rationality
- Heterogeneity of agents

MLAP 6.3.1 Bounded Rationality

- Given so many predictors, agents will not account for all of them without incurring some cost
  - Ch 5 looks at this wo micro foundation
- Models can look at which predictors investors will focus on and how this affects return predictability
  - In the past certain predictors were more costly to observe than now, how does this affect return predictability of a current econometrician

MLAP 6.3.2 Heterogeneity

- Ch 5 assumed homogeneous investors
- By assuming heterogeneity in an ML setting:
  - Model sophisticated investors solving the HD problem versus noise traders
  - Investigate heterogeneity amongst sophisticated investors (e.g. specialization)

Conclusion

- ML can be applied to both empirical and theoretical asset pricing research
- For empirical, the goal is to determine which methods work best specifically in the areas of regularization, interactions and structural change
- For theory, ML can help us get closer to the real world HD decision problem investors face as well as the way in which they learn over time
- Thoughts?