Dylan Zou

Stat 362 Final Paper

Can HANKs Learn? Investigating Machine Learning's Impact upon New Keynesian Models

Abstract: This paper investigates the impact of Machine Learning (ML) methods upon New Keynesian Models and particularly around how the models construct agents' behavior and rationality. Traditionally, HANK has suffered from the forward guidance paradox, wherein HANK models fail to explain the indirect transmission effects of monetary policy. Through the investigation of Heterogeneous Agent New Keynesian models using ML techniques such as Stochastic Gradient Descent and Neural networks, I assessed ML techniques based on their ability to optimize, estimate, classify and/or predict functions, patterns or variables. The success and flexibility of neural networks in modeling Heterogeneous Agent New Keynesian models, especially in neural network models that are built to represent potential non-linearity and high-dimensional values, suggest that neural networks models are most effective for HANKs.

Introduction: As Acharya and Dogra (2020) note, the original HANK or heterogeneous agent new keynesian model was first formulated by Branch et McGough (2009) in the context of the 2008 financial crisis when faith dwindled in economic orthodoxy. Since then, Heterogenous New Keynesian Models have become central to modern monetary policy from Central Banks to Policy Makers for its incorporation of heterogeneity and uninsurable idiosyncratic risk. Economists aim to either build upon or test the assumptions of Heterogeneity through specifying and appending onto HANK via models like Acharya and Dogra's PRANK (2018) or Eskelinen's THRANK. However, other approaches rely on behavioral approaches to agents, or much more recently through deep learning which I argue is the most promising. **Traditional Approaches to HANK:** Economic literature on HANK often foregoes ML methods, often formulating their models through reference to and modifying from traditional economic equations that is then cross-compared with data. A key concern in much of the literature centers around how HANK is able to explain forward guidance's transmission impact from monetary policy to households, which traditional Keynesianism attempts to explain via the intertemporal consumption Euler's equation (Kaplan et al, 2018). Kaplan et al. (2018) first validates HANK by demonstrating the empirical validity of its distributions of household wealth due to its representation of income and liquidity, troubling traditional models which rely on intertemporal substitutions exclusively to explain forward guidance. Eskelinen (2021) attempts to add onto HANK by developing the household differentiating model THRANK to explain the indirect impact of forward guidance, whilst Acharya and Dogra (2018) attempts to isolate the effects of intertemporal substitution via differentiating between procyclical and anti-cyclical risks. In Gabaix's much applauded Behavioral New Keynesian model (2020), Gabaix is able to completely discard forward guidance via cognitive discounting which characterizes the agent as partially presently interested. Pfauti and Seyrich's (2021) builds upon Gabaix by explaining the consumption effects of monetary policy through cognitive discounting and bounded rationality. **New Approaches:** Much of the research on Hank is predicated upon discovering variables and complicating the assumptions of existing ones. Susan Athey writes that ML could potentially have an effect on the estimation of heterogeneity (Athey pg.2, 2018) through cross-validation and causal forests.

Attention on complicated agent behavior as expressed through the potential myopia of cognitive discounting agents but also the heterogeneity of heterogeneous households in their differential responses to shocks and intertemporal substitution. Maliar et al (2020) attempt to address the dynamism and dimensionality of three economic equations through the use of neural networks and deep learning. Increased attention towards the New Keynesian criticisms of central banks' understandings of expectations through the rational agents and imperfect information have increased interest in self-referential models and how beliefs affect demand and expectations through the data-generating process (Eusepi and Preston, 2016). In an attempt to account for the high-dimensionality of heterogeneous agent models, Han et al (2022) use deep learning to create an algorithm to assess the accuracy of heterogeneous agent models. In a similar vein to the behavioral turn paved by Gabaix, Chen et al. (2021) attempt to create an artificially intelligent agent HANK model to mimic the importance of learning upon economic decisions. Kase et al. (2022) uses neural networks to demonstrate the efficacy and flexibility of ML on high-dimensional HANK models despite relaxed assumptions on bounded rationality. In the third chapter of Kase's thesis (2021), Kase demonstrates an additional ML application by showing how commonly used economics standard value function iteration algorithms can be viewed as recurrent convolutional neural networks. Even before Kase's research findings, Susan Athey suggested that the deductive, data-driven approach of ML in comparison to the inductive principle-based model selection process of economics could provide many advantages (pg.2, 2018). This can help bridge the gap between policy perception and actual data; Stempel and Zahner (2022) use a New Keynesian model combined with a neural network to find that southern Europe faced disproportionate inflation policy attention

Branch and McGough (2009) (HANK with bounded rationality and heterogeneity): This paper made in the aftermath of the financial crisis articulates an unsupervised HANK model incorporating bounded rationality with strong restrictions, heterogeneous expectations, and idiosyncratic risk to predict economic variables. The paper's formulation of heterogeneous bounded rationality is predicated on an assumption that agents are half adaptive learning, wherein expectations are forecasted by linear rules with parameters that are updated by recursive least squares (pg. 1038), and half rational, which led to a reformulation of key variables predicting the structure of the economy, such as households and monetary policy impact.

Maliar et al. (2020) (Deep Learning Using Neural Networks and SGD): This paper attempts to solve economic models using an optimizable, unstructured and unsupervised Neural network model containing non-linear regression functions that represent equations. Using Python and Google Tensorflow platform (pg. 85), this model contains hidden, linear and sigmoid layers to represent economics' unstructured and high-dimensional data. Using Monte Carlo simulation, the model uses an expectation operator to approximate integrals to approximate shocks and determine decision functions. By the models' selection of grid points based on optimized parameters and subsequent Stochastic Gradient Descent (SGD) to train the randomly selected grid points, an ergodic set converges to the solution.

Han et al. (2022) (Iterative Deep Learning Using Neural Networks and SGD) : Borrowing from Maliar, this unsupervised neural network model attempts to create an algorithm to solve heterogeneous agent models like HANK. DeepHAM is an iterative procedure that starts by introducing generalized moments for model reduction, updating the value function using a parameterized neural network for eventual optimization through stochastic gradient descent (pg. 10-14). Like the first model, it relies on optimal parameterization through SGD to achieve a convergence towards accuracy as the model operates.

Kase (2021) (Recurrent Convolutional Neural Networks): Like Maliar's attempt to represent economic functions as layers in Neural networks, Hanno Kase uses a simple heterogeneous agent model alongside a backpropagation algorithm premised on automatic differentiation principles to compare representations of Heterogeneous agent models to Neural network models. The example Kase chooses to represent this process is the distributional similarity between regular functions' arg max and neural network's softmax, which can be revealed by applying an endogenous grid method to value function iteration algorithm.

Chen et al. (2021) (Deep reinforcement learning model SGD): Instead of HANK, Chen et al. uses a dynamic stochastic general equilibrium model to predict economic characteristics. This paper used codes that rely on Pytorch and used Adam as the stochastic optimizer. First, a Neural Network was made to approximate policy solutions based on HANK models with a Stochastic Gradient optimizer. Then a Neural Network based on a Bayesian probability estimation algorithm was trained on first the entire parameter space then the result of the Neural Network particle filler model to obtain the likelihood at chosen points and minimize the loss function. By reconceptualizing expectations, bounded rationality, through the steady-state growth of rationality for artificially intelligent agents, the authors then map the model onto 12 parameter HANK or RANK models with or without parameters such as zero-lower bound to then compare household accuracy with conventional models.

Kase et al. (2022) (HANK Neural Networks) In Hanno Kase's co-authored paper, the authors use a supervised neural network model and approach to estimate a non-linear quantitative HANK model. Attempting to circumvent the curse of dimensionality and the Monte Carlo filter likelihood function of nonlinear functions, the authors create an extended neural network model with parameters that act as representative pseudo state variables that capture HANK dynamics. Then, in contradistinction with conventional global approaches which restrict the scope of estimation by resolving at every parameter draw, a RANK model that features aggregate non-linearity is then used to estimate results. At the end of the paper, the authors use a non-linear HANK model with idiosyncratic and aggregate risk using 12 parameters to estimate how true a parameter is. The authors ultimately suggest that aggregate data can only "marginally" pin down the degree of heterogeneity (pg. 4).

Deak et al. (2023) (HANK Deep Learning Model): Like the neural network models of papers previous, this paper attempts to use unsupervised non-linear, linear, and deep learning HANK models each based on rationality growth factors of differential shape to first estimate and predict and then compare the economic performance of each model. The deep learning of Deak et al.

introduces a potential "chaos' ' problem as the deep learning suggests that if agents are able to learn through anticipating utility that exogenous shocks are good for welfare (14-15).

Chen and Chang (2012) (HANK Machines and Network-Based Model): In contrast to the optimization neural network techniques of the previous two papers, this paper uses parameterized nonlinear machine models inspired from Ant Networks and Boltzmann-Gibbs under a dynamic stochastic general equilibrium New Keynesian model to construct the probability density distribution of herding behaviors. Through measurements of cross entropy, relative entropy, the Kolmogorov-Smirnov statistic, this paper attempts to characterize the distribution of social behavior within a HANK model (pg. 14-22).

Stempel and Zahner (2022) (Regressions, KNN, trees, others) : This paper attempts to use supervised models to predict a variable's weight with respect to the dependent variable of inflation weight. Using functions to represent economic processes and calibrating them with already existing inflation studies, they log transform the calibrated data and train the data on a simple neural network, multinomial logistic regression, penalized linear regression, ridge regression, various trees, and a random forest to classify accuracy (pg. 18).

Jump et al. (2019) (Deep reinforcement learning): This paper uses a deep reinforcement learning HANK model that learns via Activated Utility to estimate the weight of the Taylor condition, in order to classify whether a Taylor condition is sufficient for determinacy and stability in the context of a New Keynesian model. The model represents agents through a reinforcement learning HANK model that optimizes on bounded rationality to maximize their anticipated utility (AU) in order to ultimately predict the weight of rational expectations upon determinacy and stability.

How I measure success: I attempt to measure success by model performance in the model's ability in delivering the desired result of the study, whether it be optimization, estimation, classification and/or prediction of functions, patterns or variables. I will also be weighing the flexibility of the model, and whether it can be applied in more than a specific context like linear regression or bounded rationality.

Results and Comparisons: Overall, the studies in question used a variety of methods for a variety of different procedures. Many studies used the Stochastic Cost Gradient algorithm for optimization, whilst others simply used adam. Deep reinforcement learning seemed overall to generate very strong results, with Chen's paper (Chen et al, 2021) finding that deep reinforcement learning's ability to solve DSGE models was stronger than adaptive learning's capability to solve them (pg. 1). For other instances of Deep Learning success, the DeepHAM model created by Han et al. (2022) is a global solution model that optimizes the policy function in models assuming heterogenous agents. As Han et al. (2022) writes, the model "does not suffer from the curse of dimensionality" (pg. 1), but also solves the constrained efficiency problem (pg. 16-18) in addition to the Krussel-Smith model with "all results… statistically significant" (pg. 19). Jump et. al. (2019) presents a modest finding through a deep learning model that supports economic orthodoxy by upholding the sufficiency of the rationality expectations (pg. 465). However, Deak et al. (2023) argue that a deep learning HANK model led to a striking result which seemed to imply that increasing the volatility of exogenous shocks was welfare-increasing for the reason that it assisted the learning process and rationality growth of fully rational agents (pg. 1). However, across the spectrum of supervised versus unsupervised, linear versus non-linear, simple versus complex, Neural networks have been used to great efficiency in almost all of the studies' methodology. Maliar et. al (2020) and Han et al. (2022) both demonstrate that complex and deep Neural Networks can provide a global solution via Stochastic Gradient Descent to economic functions. Maliar directly states the advantages of Neural networks in their paper too, recognizing that they are "linearly scalable, robust to ill-conditioning, capable of model reduction and well suited for approximating highly nonlinear environments including kinks, discontinuities, discrete choices, switching." (pg. 77). In a perhaps unorthodox investigation of HANK using ant-networks and Boltzmann-Gibbs particle behavior in Chen and Chang's (2012) paper, HANK's distribution was found to resemble the distribution of herd behavior within a relative entropy distribution of less than .5 (pg. 22). But perhaps the strongest evidence lies in the studies that use Neural Networks alongside other models. In Stempel and Zahner, even a simple neural network performed on a linear, supervised model blows all the accuracy scores of the other models out of the water, with an accuracy score of .97 compared to below .5 for the other models including KNN (pg. 18). The fact that neural networks often constitute many deep learning algorithms (Chen et al, 2018) throw a wrench in a potential assumption of independence for the effectiveness of deep learning as compared to neural networks. In a similar vein, Stochastic Gradient Descents are often used alongside neural networks as optimization models (Maliar et al, 2020). Overall, the widespread use and efficacy of neural networks in various contexts strongly suggests its predictive, optimizing and classification power in the context of a non-linear HANK model. **Applications:** Promising new research by Hanno Kase (2021) and Maliar et al. (2020) open new inquiries on the relationship between economic functions and neural networks, such as the Euler and Bellman equations subsumed into a neural network in Maliar et al. (2020). For what this means for HANK, a model with many multiple shapes, dimensions and representations that find it hard to be expressed through conventional economic means, will perhaps find more fruitful applications in a deeper investigation using Neural Networks. As Susan Athey (2018) suggests in her "four themes" (pg. 1-2), ML can not only provide an answer to approaches in economics by its lack of concern for "identification" (pg.1), but by the fact that it holds sacred model comparison and metrics of confidence intervals (pg. 2).

Conclusion: So can HANKS speak? If so, surely its agents must speak through neural networks. In my introduction, I trace the gradual evolution of HANK literature from its popularization in the crash to its ML models. By reviewing ten papers from the Heterogeneous Agent New Keynesian literature, I argue that neural networks are not just the most effective model in tasks relating to HANK models, but based on the evidence, its efficacy and wide range of applications suggest that it is the best approach to represent HANKs. Neural network models are thus also the most likely to aid in answering the forward guidance paradox, as Acharya and Dogra (2018) and Eskelenin (2021) have attempted to.

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