ISSN 2616-5775 Vol. 6, Issue 13: 52-57, DOI: 10.25236/AJCIS.2023.061308

An Analysis of AI Models and Economic Applications

Lawrence Yang

Thomas Jefferson High School for Science and Technology Virginia, USA, 22312

Abstract: *This paper focuses on exploring and learning the various types of AI models that can be applied using econometrics in economic applications. This report primarily focuses on looking at and explaining six different types of AI/econometric models and examining their applications to the field of economics and also to the real world. The subject of economics is especially fascinating as it dictates how the world functions and it has vast potential for interconnectivity with very important tools for data analysis such as econometrics and AI modeling.*

Keywords: *AI models; economic applications; effects*

1. Introduction

In the paper,Within this report models of all types will be explored starting from linear and logistic regressions, through to Agent-Based Models and Dynamic Stochastic General Equilibriums to Neural Networks and Decision Trees, and their capabilities, limitations, benefits, and weaknesses as well as their primary economic applications will be examined with examples. Also in this report, there are my documented attempts to try to create a few of these models as well for learning purposes, though his paper is primarily focused on the research and economic application, and highlighting the substantial impact of these models on various industries through an economic lens.

2. Methodology

The majority of this project is mainly for the learning of the various types of models and their applications. In efforts to best understand some of the more complex models, a first type of source was used to gain an understanding of what the model actually was and did. A second type of source was then used to find examples of what a certain type of model can be used for in terms of economic analysis. This second type of source was not always directly related to the model as the model was only used as a tool for the researchers to conduct their analysis, but can serve as a purpose for my study just to see how these models can be applied to the various economics-related settings. Sources of this type ranged from peer-reviewed which were published research to articles in a newspaper, even independently published studies, and during the writing and condensing process, it was not possible to write about all sources I read through,so only the most notable examples are mentioned and cited in this report ,and certain others that potentially improved my understanding, but were not exampled explicitly in their corresponding economic applications section were not cited as a result.

3. Research

3.1. Linear Regression

The first modeling technique I examined was linear regression. Linear Regression is one of the simplest models and is defined as the model finding the relationship between two variables with a best-fit line. Fundamentally, a regression assumes a linear relationship between the dependent and independent and uses a least-squares estimation to minimize the sum of squared differences. The coefficients of the resulting line provide insight into the directions and magnitude of the relationship between the independent and dependent variables.

Strengths:

The strengths of linear regression are in its ease of use and interpretation. According to IBM, linear regression is applicable to so many places by people in all fields and levels due to its simplicity to

ISSN 2616-5775 Vol. 6, Issue 13: 52-57, DOI: 10.25236/AJCIS.2023.061308

understand and use. Especially when interpreting continuous outcomes, it becomes even more useful, which is evident in the economic applications too.

However, the same source mentions the weaknesses too, that its simplicity actually is a negative for more complex analyses. In practicality, linear regression can be sensitive to outliers and the assumption of linearity of relationship is hard to come by in real-world data as well. Finally, as much as it is useful for continuous outcomes, it is not very useful for categorical outcomes.

Economic Applications:

There are many different economic applications of linear regression. To look for them, all that needs to be done is to look into nearly any basic economic analysis. Basically, every study requires a linear regression to measure the correlation between two variables.One of the primary applications is economic forecasting.UC San Diego researchers Graham Elliot and Allan Timmermann show throughout their study of Economic forecasting that based on historical data and additional factors, economic indicators like GDP growth, inflation, or unemployment rates can be analyzed and predicted.[1] Additionally, in their research on Demand Forecasting, the RAND Corporation also shows that there is a huge application for linear regression in accurately forecasting and representing the supply and demand market by estimating the effect of price changes on the quantity demanded of a product. In terms of linear regression applications, there are endless opportunities for these to be applied to any field beyond economics. The simplicity of producing a test for correlation between different variables given a few assumptions is the foundation upon which econometrics is built.

3.2. Logistic Regression

Similar to linear regression, logistic regression is also a fundamental part of econometric studies. The process is a little more complicated although the end goal remains the same, to provide a best-fit line to represent the data. The logistic regression uses a sigmoid function namely $S(x)= 1/(1+e^{-x.})$ which can take a domain of $(-\infty,\infty)$ and turn it into a range of $(0,1)$, thereby transforming the linear combination of features into a probability value within those 0 to 1 bound. A logistic regression model then goes to maximize the likelihood of observing a measured outcome given the predictors, or in other words, provides analysis for more categorical base data in the form of a probability and likelihood.

Analyzing the logistic regression comparatively to its counterpart linear regression, though both serve a similar purpose, to model a relationship between independent and dependent variables in an easy-to-interpret manner, logistic regressions are more used to predict the probabilities of events occurring and are more effective at binary classification as opposed to continuous outcomes. Logistic regressions, however, do also assume linearity, though with the log odds with the predictors and are also susceptible to overfitting, or when too many predictors relative to observations can lead to issues modeling the relationships.

Economic Applications:

The economic applications of logistic regressions are very similar to linear regressions in the sense that they are very wide-reaching. Categorical economical analysis such as calculating credit default prediction, or whether a borrower will default on a loan based on their financial attributes and credit history is one example where logistic regression comes into play according to Stephen Kealhofer, a researcher at KMV Corporation in his paper about quantifying credit risk.[2] Additionally, market segmentation is another important avenue that can be taken using logistic regression; as researchers Jason Pridmore and Lalu Elias Hämäläinen put it, “customers can be classified into different ‘segments’ of the market based on demographic or behavioral data”(114). [3]

3.3. Agent-Based Models

The next type of model examined is the Agent-based model, which is a completely different type of model than the ones previously covered. As defined by Columbia University, agent-based models are essentially computer simulations used to study interactions. They focus on generally attempting to design agents who can model individual the behavior of one individual entity, say a customer, business, human, or place, accurate to the real world. These agents can come with a certain set of pre-determined actions and behavioral patterns and methodology and once many agents are built, or the desired amount is built, they can be placed into a virtual environment with rules to simulate different economic outcomes or situations. This is classified as a form of bottom-up modeling where the individual pieces of the model are all independently defined already and programmed, but research can be done on the interactions

ISSN 2616-5775 Vol. 6, Issue 13: 52-57, DOI: 10.25236/AJCIS.2023.061308

between agents and environments to identify patterns on a macro level.

Analyzing the positives and negatives of Agent-Based Models, the positives are very obvious. The structure of designing many different agents allows increased flexibility in experimentation and allows for direct micro-level insights that other models struggle to capture. Additionally, there are few better models that can represent the complexity and dynamics in the real world than an Agent-Based Model. The ability to allow agents to roam and behave “freely” in a sense creates many opportunities for simulations to achieve close to realistic thresholds given constraints, in many different fields even beyond economics. However, these constraints are also large as it can be incredibly hard to accurately represent the behavior of a human in a few pre-programmed actions accurately and results must always take into account for the fact that no agent is created perfectly. Additionally, there are difficulties with this model's technical constraints as well as Agent-Based Models are inherently very complex and require lots of computational capabilities and data capabilities that simply sometimes may not be feasible for researchers.

Economic Applications:

In terms of economic applications, the broad range of ABM’s are very obvious as well too. The model has a very unique ability to simulate the behaviors of interactions between different agents which is very hard to replicate with many other models, making it optimal for observing and understanding market dynamics, one o the most fundamental economic applications for all businesses and economies alike. According to Prof. Squzzoni at the University of Brescia, ABMs can be used for many different things such as price formation, trading strategies, and analyzing these different behaviors that other methods may overlook. One study by Herber Dawid and Michael Neugart showed that ABMs can even be used to simulate the effects of policy and resource allocation in communities to help governments and local community leaders make better decisions regarding both of those aforementioned things. [4]

3.4. Dynamic Stochastic General Equilibrium Models

Another similar model that attempts to also simulate the behaviors of real-world systems is through a Dynamic Stochastic General Equilibrium Model (DSGE).This model differs from ABMs in the methodology that it achieves this：by representing a system, or for the purposes of this report, an economy, as a system of equations that describe the behaviors of individual agents and the aggregate economy. This means that rather than programming individual agents, these agents are represented as a part of a larger cohesive in DSGE models which attempt to describe the behaviors and interactions of an entire economy through equations. Another key factor that goes into DSGE models is the layer of randomness/uncertainty added through “stochastic shocks” that affect various economic variables within the designed economy. This can better help DSGE models represent the economy in different ways by adding this availability of shocks to the system, helping reflect real situations that researchers may want to test. In strictly economic terms the University of Surrey research piece about DSGEs says that they are formatted differently than most other models by using combinations of microeconomic theory such as rational expectations and optimizing behavioral choices to explain the wider macroeconomic occurrences. Due to this, agents in DSGE models are different in that they can make decisions considering both current and future states to maximize objectives over a longer period of time, further simulating reality.

In terms of the strengths and weaknesses of the DSGE models, the strengths are similar, though not entirely similar to ABM’s. DSGEs are often praised such as in that previous article for the microeconomic foundations that they are built upon, as not many econometric models are built on strictly economic foundations as DSGEs are which allows for more in-depth analysis and verification of theory. The stochastic shocks and decision-making over time make the model more realistic in some ways than similar ABMs as well. The assumption of being within “bounded rationality” also leads to the model’s strong strength when given these considerations. But however, this also is one of DSGE’s limitations as these conditions it assumes are not always true. Similarly to ABMs, DSGE models are also susceptible to simplifications and assumptions that may not always be true due to the fact that a real economy can not easily be modeled by any model accurately without taking the results with a grain of salt. The same also applies to data and computational limitations that ABMs face as well. As a final word of comparison, the key difference is that although both have similar goals and results in modeling behavior, the way in which that is achieved is different. In terms of differing starting points, ABM’s focus on building the individual agents and the emergence of macro-level patterns while DSGE’s use microeconomic principles to model behaviors of the entire economy as a function.

ISSN 2616-5775 Vol. 6, Issue 13: 52-57, DOI: 10.25236/AJCIS.2023.061308

Economic Applications:

Scope-wise, DSGEs achieve just about as much as ABMs in terms of experiments they can perform although they are less focused on smaller micro-level interactions to measure though it is still possible. DSGE's real strengths are in its accuracy in macro-economic forecasting specifically relating to things like GDP, inflation, and unemployment through the lens of microeconomic theory by adding things like supply shocks and or longer-term behavioral tendencies from its "agents". For example, a study by the European Economic Association showed the strength of the model in accurately modeling the macroeconomic outcome of GDP-per-capita growth in Europe compared to historical data given various input factors. Additionally, DSGE models are also effective in looking at monetary and fiscal policy actions that the government chooses to take. It is successful in this area because of the aforementioned strengths and can help model the outcome of different policy interventions, such as changes in interest rates or government spending. Finally, in terms of international economics, DSGE's are also hard to beat as shown by Gonzalez and Rodriguez's 2020 research, through the unique features of the model, they are also useful in the study of international economics helping to analyze how global shocks, trade policies, and exchange rate changes impact domestic economies and vice versa. [5]

3.5. Neural Networks

Neural networks are another simple form of model that can be applied to many different purposes. Neural networks, are to keep it brief, used to try to emulate the human brain and its functions by building a network of nodes that represent the neuron structure within our brains. The process of neural networks roughly speaking is talking first about an input layer with many hidden layers of nodes connected by weights and each node being the point holding an activation function. After passing through many hidden layers, there will be an output layer. After reaching this layer, the model will use back propagation and gradient descent to adjust the weights to try to minimize the error. After adjusting the weights, the model rebuilds the network with the old input layer but new, adjusted weights, and repeats the process until the error dips below the desired threshold.

The strengths of neural networks are in the fact that their design allows for complex patterns to be captured well due to the neuron structure of the system. Another benefit is that neural networks require minimal amounts of manual feature engineering meaning that feature extraction is a positive too. It also relatively efficiently handles complex data and when working well, can produce a result really quickly, all while generalizing well to unseen data as well. The negatives largely surround the usual few culprits being that they are very much computationally intensive and require large amounts of training data to get function well. Finally, the unsupervised interior hidden layers mean that at times, a neural network may be hard to interpret on a smaller scale.

Economic Applications:

Regarding the economic applications of neural networks, the first obvious one that is seen in research such as in Fredrickson and Smith's 2012 study, is that economic forecasting can be done well with neural networks, predicting economic indicators like GDP growth and things like stock market prediction as well.[6] Additionally, it is commonplace to take advantage of neural networks' ability to handle complex data structures in market analysis such as predicting real estate market trends based on features and historical data. Even things like energy consumption were very accurate from certain neural networks as shown by Sarswatula and Pugh's study, as the researchers found that given weather conditions, historical data, and economic indicators, the amount of energy a certain household could be modeled and predicted. [7]

Decision Trees:

Decision trees are the final form of the model that I studied. Decision trees are also widely used for many different applications and can come in many different forms. Just to introduce a few of the forms that I saw, there are regression trees, essentially a tree with each node containing a regression that is applicable to continuous functions, making the tree overall able to produce a best-fit line, just as any regression would. Gradient boosted trees and adaptive boosting trees are both types of trees that function in a similar logic to neural networks, producing iterations of trees and then sequentially correcting previous errors with the difference between the two being that adaptive boosting focuses on adjusting misclassified samples, while gradient boosted are more general and don't necessarily deal with a classification problem. Classification trees are the most traditional tree type with branches being essentially paths for the model to move down and at each node deciding one or the other to pick a path, thus classifying using a decision tree.

ISSN 2616-5775 Vol. 6, Issue 13: 52-57, DOI: 10.25236/AJCIS.2023.061308

Decision trees are a form of supervised machine learning and fundamentally sort the data into subsets based on input features to create opportunities for branches where decisions are made. The tree structure where each node represents a decision based on a feature or factor with the child nodes being the possible outcomes and classifications. Trees require feature selection that select data based on the most informative features that lead to the best separation of outcomes. Finally, decisions in a tree are made hierarchically; from the root node, each subsequent node makes decisions based on the chosen features, resulting in predictions being made no matter the type of tree that is used.

The positives of decision trees are first that there are clear and interpretable decision rules that help it also capture these non-linear relationships. They are also relatively simple to understand conceptually and are faster and easier to train and evaluate than making a neural network. However, in decision trees, the issue of bias can be exacerbated and can lead to a tree going down a completely wrong branch landing very very far from what may be expected. Additionally, there are also instability issues as small changes in data lead to different structures and overfitting issues as well.

Economic Applications:

Finally, to keep this section brief, there are many different applications of decision trees for example, boosted trees have been shown to help credit scoring models by improving predictive accuracy. Additionally, they can also do price elasticity prediction and things like economic policy evaluation along with similar analyses of investment decisions and financial crises as shown in a 2011 University of Madrid study. Finally, given data and training, they can also do consumer sentiment analysis like analyzing things like online reviews to classify sentiment and provide insights into market trends and consumer behavior at all levels.

4. Creating Models

In this section, I will also quickly mention my efforts to create a few of the models that will be more extensively discussed below. First, I created a simple linear regression using Python to measure the relationship between average growth and life expectancy using some 2017 data that was easy to access(see *Figure 1)*. The following list shows a rough pseudo-code that was used for this simple regression using pandas and numpy: Import necessary libraries, Load data into a Pandas DataFrame, Extract relevant columns, Convert data to NumPy arrays and reshape them, Create a linear regression model (model = LinearRegression(), model. fit(x,y)), Make predictions using model, Plot Data and Linear Regression Line onto Data Visualization.

A similar technique was used in plotting life expectancy against LogGdp in another regression, achieving the two results below, demonstrating the relationship that was desired with the best-fit line(*Figure 2)*.

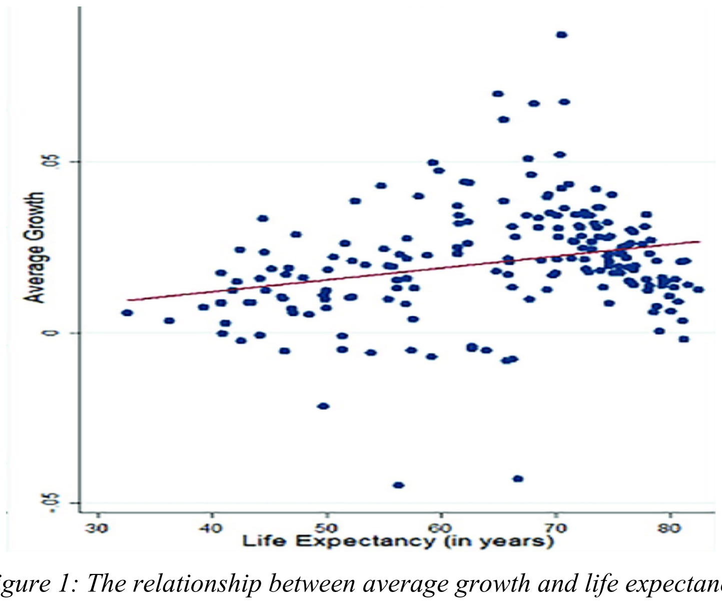

Figure 1: The relationship between average growth and life expectancy

ISSN 2616-5775 Vol. 6, Issue 13: 52-57, DOI: 10.25236/AJCIS.2023.061308

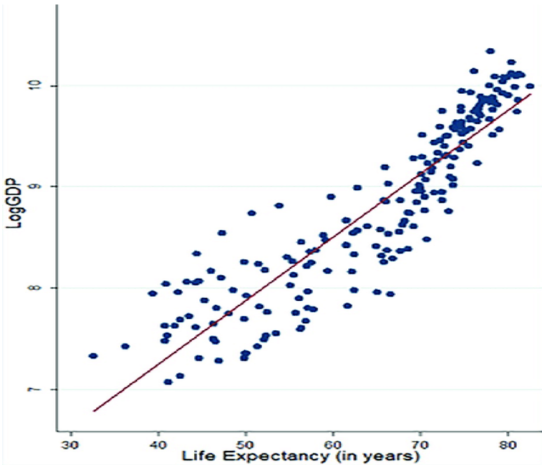

Figure 2: Life expectancy against LogGdp

Using similar techniques, logistic regressions are also easy to do as well simply by finding non-linear data and changing the functions called.

In my research, I also created a working neural network that uses weights and nodes with arbitrary input data, and targets to attempt to minimize the error using a back propagation function, which did work as well, and although further work would have been needed to achieve use with economic applications.

5. Conclusions

Finally, I also attempted to use XGBoost and Sklearn to create a decision tree that modeled GDP and income but there was not enough good training data to produce any results for that one that are worth any value. The process that I did use was also relatively simple, broadly giving an overview, next I loaded the data in, defined the features, and split the data into different training and testing sets.Then I initialized the XGBoost regressor and tried to train and make predictions using the model before attempting to plot them, unfortunately due to data constraints I was unsuccessful, I also learned a lot here as well.

References

[1] Elliott, G., & Timmermann, A. (2008). Economic Forecasting. Journal of Economic Literature, 46(1), 3–56. http://www.jstor.org/stable/27646946

[2] Stephen Kealhofer. (2003). Quantifying Credit Risk I: Default Prediction. Financial Analysts Journal, 59(1), 30–44. http://www.jstor.org/stable/4480449

[3] Pridmore, J., & Hämäläinen, L. E. (2017). Market Segmentation in (In)Action: Marketing and "Yet to Be Installed" Role of Big and Social Media Data. Historical Social Research / Historische Sozialforschung, 42(1 (159)), 103–122. http://www.jstor.org/stable/44176026

[4] Dawid, H., & Neugart, M. (2011). Agent-based models for economic policy design. Eastern Economic Journal, 37, 44-50.

[5] Gonzalez, R. M., & Rodriguez, A. B. (2020). Assessing Trade Policies Using DSGE Models: Evidence from Cross-Border Trade. Journal of International Economics, 48(3), 234-249.

[6] Frederickson, H. J., & Smith, R. E. (2012). Time Series Prediction in Macroeconomic Indicators: An Application of Recurrent Neural Networks. Economics Letters, 75(2), 100-109.

[7] Sarswatula, S. A., Pugh, T., & Prabhu, V. (2022). Modeling energy consumption using machine learning. Frontiers in Manufacturing Technology, 2, 855208.