* **Question 2**

1. Integration of behaviour economics with machine learning and applications.

**Answer**. **Behavioural economics---** method is a detailed analysis of human behaviour to explain economic decision marking natural limits of human on computation, willpower, self-interest and implications of those on economic decision/ choices

**Machine learning** is a “supervised” learning that revolves around the problem of prediction it provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning manages to uncover similar patterns. In fact, the success of machine learning at intelligence tasks is largely due to its ability to discover complex structure that was not specified in advance. It manages to fit complex and very flexible functional forms of the data without overfitting it finds functions that work well out-of-sample. The main focus is the development of computer programs that can access data and use it learn for themselves.

Machine learning can be used in search for new behaviour pattern which may affect the choice of individuals and may affect the firm financially. Poor implementation of machine learning leads to poor human behaviour predictions. Also one can look for the implementation of AI in firm to understand human behaviour and exploit human limits which can be understood from behavioural economics about attention, nature and perceived fairness.

Behavioral economics is recast as open-mindedness about what variables might predict. Then ML is an ideal way to do behavioral economics because it can make use of a wide set of variables and select which ones predict the best.

**Bargaining**: There is a long history of bargaining experiments trying to predict what bargaining outcomes will result in variables using game theory. It suggested that the time, delivered sharp, non-obvious new predictions about what outcomes might result depending on the structural parameters—particularly, costs of delay, time horizon, the exogenous order of offers acceptance, and available outside option. Most natural bargaining is not governed by rules about structure as simple as those theory and experiment became focused. Natural bargaining is typically “semi-structured—that is, there is a hard deadline and protocol for what constitutes an agreement, and otherwise there are no restrictions on which party can make what offers at what time, including the use of natural language, face-to-face meetings or use of agents, and so on

To predict whether there will be an agreement or not based on all variables that can be observed. From a theoretical point of view, efficient bargaining based on revelation principle analysis predicts an exact rate of disagreement Machine learning is able to find predictive value in details of how the bargaining occurs How do emotions, face-to-face communication, biological measures influence bargaining? Do people consciously understand why those variables are important? Can ML methods capture the effects of motivated cognition in unstructured bargaining, when people can self-servingly.

**Risky choice**: Machine learning can be employed to analyze decisions between simple financial risks. The set of risks are randomly generated values with associated probabilities a willingness-to-pay (WTP) for each gamble. They also estimate predictive accuracy of a one-variable expected utility model (EU, with power utility) and a prospect theory (PT) model which adds one additional parameter to allow nonlinear probability weight and Machine learning are equally accurate because the ML method allows quite a lot of flexibility in the space of possible predictions. Machine learning shows huge amount of flexibility could fit, possibly to provide a ceiling in achievable accuracy. If the ML predictions were more accurate than EU or PT, the gap would show how much improvement could be had by more complicated combinations of outcome and probability parameters. But the result, instead, shows that much busier models are not more accurate than the time-tested two-parameter form of PT, for this domain of choices.

**Limited strategic thinking: S**ub-game perfection in game theory presumes that players look ahead future to what other players might do at future choice nodes. In order to compute likely consequences of their current choices. This psychological presumption does have some predictive power in short, simple games.

More generally, in simultaneous games, there is now substantial evidence that even highly intelligent and educated subjects do not all process information in a way that leads to optimized choices.

From behavioral game theory ML over structural properties of strategies can predict experimental choices. The main analysis creates decision trees with k branching nodes that predict whether a strategy will be played or not. Analysis uses 10-fold test validation to guard against overfitting. Through Machine Learning given a data set of actual human behavior, and assuming that subjects are playing people chosen at random from that set, the best they can do is to have somehow accurately guessed what those data would be and chosen accordingly

**Overconfidence:** This increase in confidence, combined with no increase in accuracy, is reminiscent of the difference between training set and test set accuracy in AI. As more and more variables are included in a training set, the accuracy will always increase. As a result of overfitting, however, test-set accuracy will decline when too many variables are included. The resulting gap between trainingand test-set accuracy will grow, much as the overconfidence.

**Limited error correction:** In some ML procedures training takes place over trials. For example, the earliest neural networks were trained by making output predictions based on certain parameters in the given set. Human judgment corresponds to poor implementation of error-correction.

Example - Suppose a college admissions director has a predictive model and thinks students who play musical instruments have good study habits and will succeed in the college. The student gets admitted but struggles in college and drops out. The admissions director could back-propagate the predictive error to adjust the weights on the “plays music” feature

Applications:-

1. AWS
2. Stock Exchange
3. Investment banking

References-

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1. Dynamic Econometric Models types, Transformation, Applications

**Answer. Econometric models** are statistical model used in econometrics. An econometric model specifies the statistical relationship that is believed to hold between the various economic quantities pertaining to a particular economic phenomenon. An econometric model can be derived from a deterministic model by allowing for uncertainty, or from an economic model which itself is stochastic. However, it is also possible to use econometric models that are not tied to any specific economic theory. he quantities being analyzed can be treated as random variables**.** An econometric model then is a set of joint probability distributions to which the true joint probability distribution of the variables under study is supposed to belong. In the case in which the elements of this set can be indexed by a finite number of real-valued *parameters*, the model is called a parametric model otherwise it is a nonparametric or semi-parametric model. A large part of econometrics is the study of methods for selecting models, estimating them, and carrying out inference on them.

Types of econometric models

* [Linear regression](https://en.wikipedia.org/wiki/Linear_regression)
* [Generalized linear models](https://en.wikipedia.org/wiki/Generalized_linear_model)
* [Probit](https://en.wikipedia.org/wiki/Probit)
* [Logit](https://en.wikipedia.org/wiki/Logit)
* [Tobit](https://en.wikipedia.org/wiki/Tobit_model)
* [ARIMA](https://en.wikipedia.org/wiki/ARIMA)
* [Vector Autoregression](https://en.wikipedia.org/wiki/Vector_Autoregression)
* [Cointegration](https://en.wikipedia.org/wiki/Cointegration)
* [Hazard](https://en.wikipedia.org/wiki/Hazard)

Dynamic models are generally models that contain or depend upon an element of time, especially allowing for interactions between variables over time. A separate idea with the same name is models that are updated over time with new data.

Econometric modeling of economic time series requires discovering sustainable and interpretable relationships between observed economic variables. Critical and constructive aspects are distinguished, and the roles of theories, instruments, and evidence discussed. A simple statistical mechanism, which could generate data with many of the salient features of observed time series, is analysed. An inconsistency between that and models fitted to the observed data, highlights the ease of critical evaluation, as against the difficulty of constructive progress. The concept of an empirical model is introduced.

Least squares and recursive methods for estimating the values of unknown parameters and the logic of testing in empirical modeling, are discussed. The tools needed for investigating the properties of statistics in economics, namely, large‐sample distribution theory and Monte Carlo simulation techniques, are described. Ergodicity is explained, as are tools for investigating non‐stationary due to unit roots.

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Regression, linear least‐squares approximation, contingent plan, and behavioural model are distinguished as four interpretations that ‘look alike’ yet have different properties. Models of expectations formation are analysed including rational, consistent, unbiased, and economically rational expectations, the last highlighting the instrumental role of expectations in achieving plans.

Nine special cases of the autoregressive‐distributed lag model are analysed focusing on important econometric problems, namely: simple‐to‐general modelling; the ‘time‐series vs. econometrics’ debate; potential theory inconsistency; non‐autonomy; the role of expectations; autocorrelation corrections; multicollinearity; and equilibrium correction and cointegration. Monte Carlo and empirical studies illustrate each case. The analysis reveals that empirical results depend on the choice of model type.

A typology of linear dynamic systems is developed, extending that for individual dynamic equations. Alternative models of systems are derived from three operations on systems, namely, contemporaneous and inter-temporal transforms, and conditioning. Methods for analyzing econometric systems

Types:

A. Autoregressive Model:

Yt = α + β0Xt +β1Yt-1 +β2Yt-2 +..+βkYt-k + et

(With lagged dependent variable(s) on the RHS)

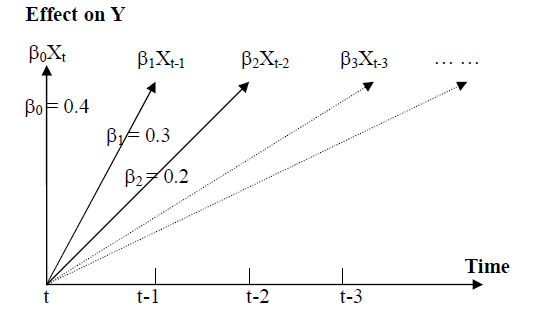
B. Distributed-lag Model:

Yt = α + β0Xt +β1Xt-1 +β2Xt-2 + …+ βkXt-k + et

(Without lagged dependent variables on the RHS)

Transformation:

Where β0 is known as the short run multiplier, or impact multiplier, because it gives the change in the mean value of Y following a unit change of X in the same time period. If the change of X is maintained at the same level thereafter, then, (β0 +β1) gives the change in the mean value of Y in the next period, (β0 +β1 +β2) in the following period, and so on. These partial sums are called interim, or intermediate, multiplier. Finally, after k periods, that is ∑i-0 βi= β01 + β2 +β3 + …+ βk =B, therefore βi is called the long run multiplier or total multiplier, or distributed-lag multiplier. If define the standardized βi\* = βi /βi, then it gives the proportion of the long run, or total, impact felt by a certain period of time. In order for the distributed lag model to make sense, the lag coefficients must tend to zero as k->∞. This is not to say that β2 is smaller than β1; it only means that the impact of Xt-k on Y must eventually become small as k gets large.For example: a consumption function regression is written as Y = α + 0.4Xt + 0.3 Xt-1 + 0.2 Xt-2 + 0.1Xt-3…+ et. Then the effect of a unit change of X at time t on Y and its subsequent time periods can be shown as the follow diagram:



Applications where it can be applied:

1. Money creation process
2. Inflation process due to money supply
3. Productivity growth due to expenditure or investment.

Refrences

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