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Fiscal Policy Simulation Using AI And Big Data: Improving Government Financial Planning

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Abstract
In almost every country, fiscal policy simulation design is crucial and challenging, since finance authorities need to prepare plans for government revenues and expenditures on a set of financial variables over time. Conventionally, such complex policy design problems are handled by experts, whose goal is to achieve the desirable control performance under a set of regulations. However, when dealing with sophisticated contingent regulations, constraints, and massive state spaces, expert knowledge may not be enough for optimal plans. This paper demonstrates a new approach that offers helpful computational tools for policy design. This novel approach views the government policy design process as a complex multi-agent deep reinforcement learning problem, where the AI Economist employs interpretable policy functions, and focuses on the design of the future AI-based policy options generation engines. To better capture policy design expressed in the control space, this multi-agent framework directly models the fiscal policy options generation process, developing both regressive and generative AI-based engines for the design of policy trajectories. Furthermore, they develop training from both on-policy samples from fiscal simulation execution and offline samples. Based on the AI Economist, this approach can hold a better chance seeking better solutions to address even those most difficult and sophisticated finance design questions.

Keywords: AI, Computational Economics, Interpretable AI, Reinforcement Learning, Policy Design, Robustness, Risk-Averseness, Simultaneous Policies, Optimal Control.

1. Introduction

Government performance hinges critically on fiscal policy, necessitating careful planning and management of receipts and expenditure primarily led by financial authorities. To achieve goals, find a balance between competing objectives, and address financial challenges, analysts simulate the budget in advance. Current methods parameterize approximative simulation of receipts and expenditure with simple functions, necessitating further refinement or coherency validation with granular information, as outside expectations are modeled by different experts in each area. Thus, this approach is complex and often infeasible. Much too detailed modeling approaches exist, which offer high flexibility, but require extensive interaction with modelers in addition to long computing times or numerical infeasibility. With the advent of AI and massive information generation, AI and big data have entered the policy planning area more concretely. Various quantitative models have been developed to improve government financial resource use through evidence-based, data-driven recommendations, covering expenditure, revenue, social welfare, and the macro economy. A series of operational tools have been designed to help policy analysts creatively simulate, visualize, clean, utilize, and create big data. This paper presents recent research on how to implement a new forecasting and controlling process based on big data and AI adopting advanced statistical learning techniques directly at the budget level in optimal data aggregation for precision and computational efficiency. As deep learning has matured in the last few years for complex process modeling at a large scale across sectors, machine learning methods are proposed to improve accuracy in estimating tax collection functions. AI-enhanced explanation and recommendation techniques are also proposed to describe practical policies and managerial strategies in an interpretable manner tailored to nonprofessional users.

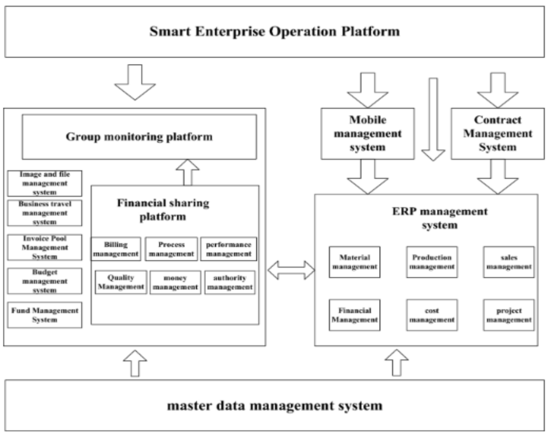

Fig 1: Improving Government Financial Planning

Section 2 formulates the direct modeling problem of main receipts and expenditure using state-of-the-art AI methods. Section 3 summarizes main modeling and management frameworks utilizing AI methods for secondary revenue sources, social policies, and economic impacts. Section 4 reviews an interactive, cross-quantitative analytical tool for fiscal policy simulation. Section 5 discusses main conclusions and ongoing and future work.

2. Overview of Fiscal Policy

Fiscal policy includes several financial policies of governments involving the budget, income and expenditure, accounting, and regulation of unit economics. It is often represented with a planned financial budget statement and includes guidance about how these plans may change under prediction errors. In this work, the focus is on a fundamental issue of how governments manage their finances given a financial policy. Specifically, this means how a fiscal policy modifies revenues and expenditures in response to a future stimulus in the public economics as a simple yet illuminating case.

Accordingly, this work shows that there is a systematic way to calculate the evolution of budgets, balances, and respective debts. For this purpose, fiscal policy is defined as how a government varies its tax rates and/or spending amounts. Given income, expenditure, and debt dynamics and an initial point, government finances must adjust to a new steady state under a fiscal policy. This adjustment, its time-course, and its effect on the flow of revenue are in part determined by the types of tax. Taxonomic criteria are proposed and implications for further exploration are suggested.

Equ 1: Government Budget Constraint

$$G_t + i_t B_{t-1} = T_t + B_t$$

- G_t: Government spending at time t
- i_t: Interest rate on debt
- B_{t-1}: Government debt from the previous period
- T_t: Tax revenues
- B_t: New borrowing

3. The Role of AI in Economic Modeling

To generate government adjustment policies in response to changing economic conditions, high-performance AI models are trained to conduct macroeconomic forecasts. These forecasts can incorporate a wide variety of factors, such as medical or demographic data, as well as predicted prosperity levels. These policies can then be run through large simulations and analysis frameworks, evaluating long-term regional growth patterns, income inequality, and even spun off to more tailored questions such as pandemic responses or tax implementations. In contrast to traditional quantitative economic models, the models use deep learning to aggregate information from data and learn hidden patterns. These patterns then become an implicit representation of the economy or agent behavior that would have been difficult to encode by hand. Most importantly, once trained, they are fast enough to be run in simulation environments in near-real-time, allowing for large data generation and evaluation even on commodity hardware. As deep learning has recently allowed for massive architecture scaling, the general policies generated are capable of generalizing across many possible changing situations.

Such models allow for rapid and accurate analysis of policies not only their static effects, but also responses years in the future as the economy shifts and develops. Coupled with a large-scale parallelized simulation environment, outputs are generated over vast regions and timescales for many policies. The results reveal broad patterns in regional and overall growth rates, accumulation of rich/poor, education levels, migration of low/high income, and many others. These patterns can be drilled down into policy specifics, allowing further models to analyze how and why certain policies give rise to certain measures. This makes it possible to obtain highly informative quantitative figures on any of the aspects in mind, from measures of fairness across different agents to outputs on how cities develop into global economies and the roles of expanded cash flow or tax deductions in wealth accumulation.

The AI framework with human-comfortable and self-explaining insights can be granted to regional advisors to aid small policy designs or local questions, as well as training regimes for more general responses that could be launched by a novel economic shock. The performance gain is evident as substantial insights are extracted corresponding to policies not even seen before, while also remaining interpretable and open to human adjustment.

4. Big Data Analytics in Government Finance

Big data has the potential to transform government finance and administration, and it has not yet been recognized by many government financial professionals in developing countries. The public sector has specific challenges, and public value is the higher objective in public organizations. Financial planning in government entails additional dimensions and complexities compared to financial planning in the private sector, such as public financial management, policies, budgets, and forecast revenues and expenditures. All these documents are prepared based on estimates resulting from analysis of big data, and the papers are generated based on these calculations. In government finance, value is not expressed in monetary terms, and hence, for setting estimation equations, fuzzy logic with knowledge graphs is more appropriate than statistical techniques.

With the growing complexity of technology, the emergence of big data analytics, and the increasing requirements for forecasting accuracy and model performance, banks, insurance companies, and other financial institutions are compelled to upgrade their forecasting systems by utilizing more sophisticated methods. Financial prediction problems are complex, nonlinear, and uncertain, but in traditional methods, all data points are processed the same, which means that bankrupt companies and highly successful companies are treated in the same manner. The adoption of big data analytics and trusted machine learning techniques in finance would fundamentally transform the way entities deal with big data. However, due to the potential impact of the AI financial market in the future, there are still challenges in guaranteeing absolute transparency of algorithm calculation and comprehensibility of models.

Fig 2: Big Data for Governance

4.1. Data Sources and Types

This simulator takes and samples a context as input from a context space. Besides, the observation space is partially observable. The government agent can only observe the variables in the red box, while the households can observe the values in both the red and blue boxes. The observation space can be summarized as: the n data points of productivity ability and asset are generated independently, uniformly, and identically from [0,1]. Then, households can observe their own productivity ability and asset, and a publicly available sample from the database summarizes the statistics of the entire population. However, other household agents are not allowed to directly observe such private information; only the total outcome can be found out from the market price. With proper reformations to the auction market, such statistics can be obtained.

The households, denoted as h1, h2,…,hN and indexed as i, firstly make their decision with ai∈Ahi, and then the government agent g1 decides with ag∈Ag1. The simulation progresses T time steps, and the output is recorded in txt format. A training set aggregates 1M data points, each with firstly recorded n×m time-sequence sample data and the corresponding n+m dimensional state values. A test set contains 300K sampled context and interleaved outputs as well, and with census-level data, the agent accuracy can be evaluated and compared with other methods.

The output organization is grain-size, flexible and customizable. When directly applied to the normal form, the reward and payoff can be totaled by collating and then aggregating data. Numerous aggregating and retotaling methods are supported, from basis functions like sum or mean over one dimension to domain-specific custom functions. The output data set can also be presented as a human-readable SQL table of customizable column orders.

4.2. Data Processing Techniques

We developed a simulated environment based on the synthesized fiscal policy specifications. This environment takes a detailed structure on income taxes, allowances, deductions, tax credits, child benefits, and transfers, as well as economic parameters such as labor supply elasticities, returns of government expenditures and effective tax rates. A fiscal policy simulation model is then used to simulate fiscal policy effects. The model is built as a system of equations and includes detailed structures on tax legislation and government expenses at different levels. The micro-level tax data were first collected to obtain demographic, labor market-related, and tax policy-related information for all working adults. For valid generalization from the conservative model to the real case, a context information environment is constructed to gather economic variables that are relevant for the model, showing intuition on how the system evolves dynamically with the observed information. These explanatory variables that keep feeding decisions have then been collected for standardization. Past decisions and states are also saved and pre-processed to obtain aggregate features for the micro prediction model.

To enable the comparison of the same agent-based models/executors and fiscal policies, a fiscal policy simulator is well designed and proposed. The fiscal policy simulator provides a detailed structure for transforming between different representations of fiscal policy and clarifies its guiding rules for the simulation and the exercise of policies. To build a corresponding simulator that can take actions of the same representation, an exhaustive design pattern is proposed to encapsulate the analyst agency, policy agents, policy environments, and platforms concretely with the required functionalities. Suggested input formats are presented for the input/output channels and data pipelines. To address the big data-loaded fiscal system during the reasonable and efficient simulation as real-time as possible. To unravel the black-box models with simple structures and instant responses to input context information sequences, the pseudo deep models such as linear regression, decision trees, and linear classifiers are utilized. To speed up the prediction of micro-level fiscal policy models, an ensemble of shallow models with selected features that best characterize the dependent variable is introduced.

Equ 2: Fiscal Multiplier Estimation (ML-enhanced regression)

$$Y_t = \beta_0 + \beta_1 G_t + \beta_2 X_t + \varepsilon_t$$

- Y_t: GDP at time t
- G_t: Government spending
- X_t: Vector of control variables

5. AI Algorithms for Fiscal Policy Simulation

Most existing works on algorithmic policy design focus either on general AI algorithms or special economic environments, and there is a gap in policy design framework that combines advanced AI methods with a general economic environment. The AI Economist aims to bridge this gap, providing an AI policy design framework that combines big data, interpretable machine learning (ML), and scalable simulation tools. The AI Economist is designed to address incentive mechanisms for a broad class of policies. It focuses on policies that can be computed macroscopically and are interpretable in social science applications, such as fiscal policy, which describes tax and transfer rules.

Policymakers encounter specific constraints while developing real-world rules, and special attention should be paid to bounding the rules or the problem itself. AI methods, such as deep learning, reinforcement learning, and simulation, can make complex modeling problems tractable [3]. Decision-making in policy design is difficult because of the extensive state and action space, real-world rigors that restrict exploration, computationally expensive environments, and the need for human-centric derive policies. While these problems are difficult for conventional models and search algorithms, AI methods can potentially help discover exceptional policies that outperform existing heuristics and complex simulation models.

The AI economist is a principled algorithmic policy design framework for complex economic problems focusing on AI methods using machine learning and simulation. Simple simulation models with closed-form equilibrium solutions have been long used in policy design for industrial organization, regulation, and finance. Precise models are less common for macroeconomics or general equilibrium models, where firms, consumers, and market-clearing prices form complex interdependent optimization problems. Very detailed representative agent models can only describe individual agents in aggregate decision-making while pricing in an input-output model.

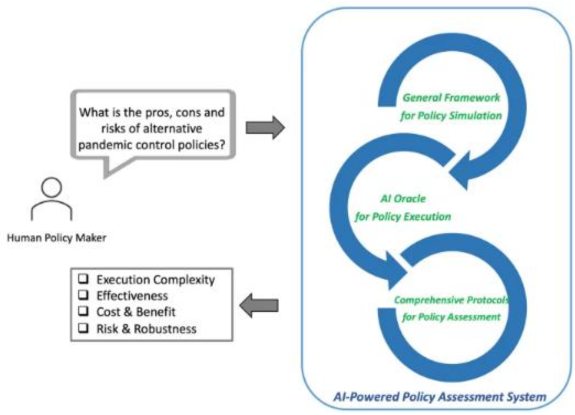

Fig 3: AI Algorithms for Fiscal Policy Simulation

5.1. Machine Learning Approaches

This chapter focuses on AI simulation approaches that aim to characterize the economy from various perspectives. Common information representation protocols are proposed for simulating ecosystems composed of multiple heterogeneous agents using reinforcement learning. High-dimensional time series data generated by agent-based models and structure prediction are employed for macroeconomic analysis and trajectory simulation. Supervised learning approaches assist the production and evaluation of economic models and scenarios, track model biases, employ translation models and identify local surprises and shocks. The input data description is discussed for the proposed AI simulator and supervised learning approaches.

Most existing economic modeling approaches rely on strong assumptions about the individuals and their representation of the economy. Overparameterization in simulation modeling can also lead to uncertainty in the representation of economic phenomena. Multiple representations or models can exist simultaneously. These specifications may differ in modeling assumptions, economic scenarios, policies, and targeted behaviors. This chapter provides a perspective that emphasizes the use of machine learning and AI approaches for model simulation, analysis, and evaluation. Structured financial policy adjustment problems with information asymmetry in an agent-based market are addressed through multi-agent reinforcement learning. The policy adjustment approach is decentralized, where each policy agent learns and updates its own policy in response to the market.

The potential of reinforcement learning to develop online financial adjustment strategies for fiscal policy is explored. The principal-based and efficiency-based design of multi-agent fiscal policy models is examined, and accordingly, a fiscal adjustment approach of joint actions over trigger rates is proposed. Illustrative experiments are proposed to validate the approach for the

SDFD model case. Future work includes the use of additional machine learning approaches such as imitative learning, feature extraction, and multi-fidelity approaches for fiscal modeling, as well as addressing affordability considerations.

5.2. Predictive Analytics

Predictive analytics, through time series regression models, will be used to estimate how significant variables affect tax revenues that need to be collected. Agricultural tax revenues are affected by agricultural production, while value added tax revenues are influenced by variables such as foreign trade and the retail price index. Moreover, M2 money supply, the total amount of tax paid, and government revenue greatly import variable effects on calculation and personal income tax revenues, respectively. All models will be tested uniformly to select the most suitable model among them, with the structures consisting of observed data and exogenous time-series variables utilized as alternative models. Externally assessed structures will also be created. Non-tax revenues and all prepared taxation models will be estimated simultaneously and recursively to give a comprehensive preparation. Estimation results are exported to Visual Basic Files and are in close imitation to communication protocol format. The remaining part of this function passes the data to the Excel file and consequently provides forecasts that need a check. Errors regarding missed taxes collected, which are also less than current receivables, are inside accuracy criteria. This trial confirms forecast checks against four different forecast standards, a firm provision and publication requirement based on date. Forecast outcomes are only compared to prior year ones, which are produced at the time of the prepared budget year. Forecast accuracies are relatively better regarding economic and other structural change cases than legal changes that do not pose much change in cash flows over projections. Prior-year reforecasts are also significantly better, with forecast output check times less than two seconds for a set of estimates with a prespecified processing order deemed necessary.

6. Case Studies of AI in Fiscal Policy

The previous section provides a brief overview of some major AI technologies that can analyze big data, and machine learning methods that can explain the analysis results, followed by a theoretical model that can simulate fiscal policies with these AI technologies using the above methods, along with the potential challenges and considerations in the simulation. To demonstrate the proposed model, two case studies using real-world data from the past decade on the fiscal policies of San Francisco and Boston were conducted. The motivation for selecting these cities as case studies is that they are both at the forefront of AI and big data research for city management, while also having the most diverse urban populations and significant shifts in government policy and budgetary planning over recent years. For each city, an in-depth analysis of possible influencing factors (addressed using big data and AI technologies), a quantification of the effect on the resultant key performance indicator (KPI) “government revenue” (using ML methods), and a parametric simulation prediction of the KPI under potential alternative fiscal policies (using the theoretical model) are provided. To facilitate reproduction of the results, the official datasets used and code used are provided as supplementary resources. San Francisco and Boston are selected as two case study cities: advocates of AI and big data for city management. Among many innovations, tightening of government spending post-pandemic and increased concern over home equity now serve as important targets of government policy. Both cities have diverse urban populations, with people of different races, ages, education, family size, and languages. Over the past decade, significant shifts in government expenditure volume and structure, coupled with shifts in affordability and social genomics, have intensified challenges faced by policymakers. Understanding these influences is crucial. Reviews of existing budgets revealed a disturbing gap: without address or explanation, the effect of fiscal expenditure on resultant government revenue was not properly considered. 534 scientifically selected influencing factors that cover all current expenditures of each department were gathered for each city to form an analysis rebuilding dataset. Then, 36 final influencing factors that jointly represent diverse social phenomena but also guarantee computational feasibility were selected. To visualize the ever-changing evolution in data volume, city information datasets were constructed, associating with plots. Finally, a bootstrapping procedure with 200 samples was used on a random forest regressor to quantify the influence of the 36 selected factors, resulting in selected expenditure structures that magnify the 2023 revenue for both cities. Unsurprisingly, wider differences in yearly revenue between different races lead to higher overall revenue, achieved by tightening ethnic spending. Housing traditionally served as a government revenue support, but that is no longer relevant. The recent shift in focus to affordability requires caution. Diversity in ethnic and housing situations should also be considered, for variables that may serve as inequitable measures often overlap with those for efficiency. To serve as control groups, predictions using the 3 selected structures were made for both cities to forecast government revenue in 2023.

Equ 3: Dynamic Stochastic General Equilibrium (DSGE)-like Policy Function

$$c_t = \alpha_1 E_t[y_{t+1}] + \alpha_2 G_t + \alpha_3 T_t + \epsilon_t$$

- c_t: Consumption
- $E_t[y_{t+1}]$: Expected future income or GDP
- AI models (like LSTM) can estimate expectations

6.1. Successful Implementations

The AI Economist was developed to automatically design governments’ pandemic response policies. There are several remarkable features. First, the AI Economist allows diverse policy objectives to be specified, is grounded in economic theory, and can represent environments with rich economic dynamics. Second, the AI Economist is interpretable. The social planner's policy designs can provide suggestions to policy makers, who can interpret them. Finally, the AI Economist's designs result in resource allocation efficiencies, allowing for more effective policy action. The use of high-dimensional data and sophisticated models is often necessary to design robust policies for intricate problems. To successfully employ big data and AI, it is crucial to address two challenges. First, a foundation for policy design grounded in the data must be developed. Second, a design framework that transmits the flexible representation power of data and models to interpretable and policy-relevant policies must be created.

As governments have become increasingly aware of the data deluge and AI advancement, they have initiated data programs, some including a focus on AI. Governments are producing massive amounts of data and are developing new data infrastructure, platforms, and programs to better leverage data. A systematic assessment of the state of the government financial management and AI and big data ecosystem has been completed. A full picture is provided of where AI and big data methods have been used for the purpose of government financial management. National and local governments' practices, some of which are very advanced, have been documented to shed light on how AI and big data methods can be or are being deployed in government financial management. Existing AI techniques have been summarized and benchmarked against problems of interest in government financial management. AI techniques have been implemented to solve financial management problems in specific regions.

6.2. Challenges Faced

Despite this proposal being a worthy recommendation for governments globally, there remain challenges before its adoption could be implementable in reality. Governments around the world are heterogenous organizations with different ways of conducting financial planning and budgetary processes. As a result, these particular AI and big data analysis methods will vary significantly based on the government in charge. This section outlines possible modifications for technological challenges, data acquisition and analysis, and computational theory challenges.

There remains a host of alternative technical options available to governments to achieve their fiscal AI simulation needs. These will influence the kind of development that could be done based on capital, time, and personnel. Technologies like Surveying and Qualitative Analytical Mechanics, Natural Language Processing, Financial Modeling, Analytics 2D and 3D, and Visualization Shading Representation Modeling, to name a few, could be adopted and utilized by governments. Each has advantages for geographies and environments. For instance, AI and big data analysis system simulations run ideally for stationary governments in non-volatile settings but would not be recommended for governments wanting to enact major structural adjustments, such as revamping tax collection structures. Tougher situations may require the use of these AI and big data forecasting techniques before potential instability is translated into information. While the former at least sets up a basis for understanding, in the latter situation these forecasting techniques need to be continuously reformulated to be useful and properly informed.

Data acquisition would be the next most important challenge. Big data acquisition challenges faced by nations differ widely based on existing data protocols. That being said, there does remain a key theoretical issue concerning the privacy of individuals' fiscal information, especially sensitive information that could expose the individual to identity theft or other forms of nefarious activities. While nascent AI systems have the potential to be built with fair simulation in mind, if poor controls currently shape gathering and use of data, these simulation systems will surely perpetuate and exceed existing imbalances. Poorly designed AI systems will as a byproduct be poorly designed, or more likely benignly nefarious, conduits of misinformation machines that aggravate inequality, decrease growth, or otherwise act against the public good. Eventually, governments, organizations, or statisticians would have to explore more ways of synthesizing data or agreeing on the use of data than before to build a properly functioning system.

Fig 4: Three levels of strategic challenges

7. Impact of Big Data on Financial Planning

Governments can make better financial, economic, and macroeconomic forecasts and projections on variables such as growth, inflation, and employment. This, in turn, aids decisions on fiscal policy. Forecasts of financial variables can also provide insights for the projections of government-financial-planning variables such as net income, net financial asset in relation to GDP, gross debt in relation to GDP, and liquidity. Governments can better allocate yearly budgets across current expenses, capital expenditures, and net lending. Due to a change in the governance body, some municipalities are testing new social policies and need to immediately find out expected financial impacts.

An EU-funded project's smarts by embedding social behavior theory in a big-data framework. The consequences of the policy are simulated and prioritized over the policies. Any public entity can employ the platform readily with sample data and easy-to-follow steps to improve financial forecasting, fiscal reinforcement simulation, and government-financial-planning automation. There is a need to take corrective actions against overly deteriorating fiscal balances in order to avoid public debt projection growth rates above acceptable levels. However, teamed with limited time and resources, these corrective actions must be short, rapid, and implementable. The consequences of some selected actions with high long-term effects need to be simulated concerning the parameters of concern. In order to primarily inform the correct decision-maker, the fiscal reinforcement simulation needs to be automated precisely and abstracting successfully. Specifically, Karsiyaka Municipality currently uses the forecasted financial variables for a determined period. It investigates fiscal reinforcement simulation and automation feasibility, first on the important budget ratio between current expenses and expenditures in order to draw attention to overly deteriorating financial health and explore the likely non-stepwise cumulative age effects of the budget change. Also, through financial forecasting and the above fiscal simulation by involving an input change, this research addresses the performance of the service planning reform in Karsiyaka.

8. Ethical Considerations in AI and Big Data

While AI and big data have the potential to transform G2G relationships, it is important to consider important ethical questions surrounding the appropriate use of these technologies. Ethical principles applicable to AI and big data, in health insurance, span five themes, namely (1) justice; (2) autonomy; (3) beneficence and non-maleficence; (4) explicability; and (5) responsibility. These five themes and their ethical considerations, as applicable to AI and big data in public policy simulation, have been further explored.

In terms of justice, the use of AI and big data may propagate existing biases, inequities, and discrimination. While using an AI algorithm may be a means of achieving more equitable treatment decisions, this result should be demonstrably and transparently achieved. In terms of autonomy, individuals may feel they have lost control over their data when it is aggregated and processed outside of their personal use. Agencies should be transparent when collecting personal data; people have a right to access it; and agencies should allow individuals to opt out of it.

In terms of beneficence and non-maleficence, AI algorithms should be designed to prioritize administrative processes that rely on AI in a manner that does not create harmful or unintended consequences. It may be possible to demonstrate through independent testing or peer review of algorithms, academic publications defensibly relying on the methodology, or both, that they mitigate possible risks and unintended outcomes. In terms of explicability, transparency and knowledge regarding the operation of AI systems are requirements for trust. It may be appropriate to apply the precautionary principle to those algorithm outputs that would result in a significant change in decision-making, and for which there are material concerns about their fairness.

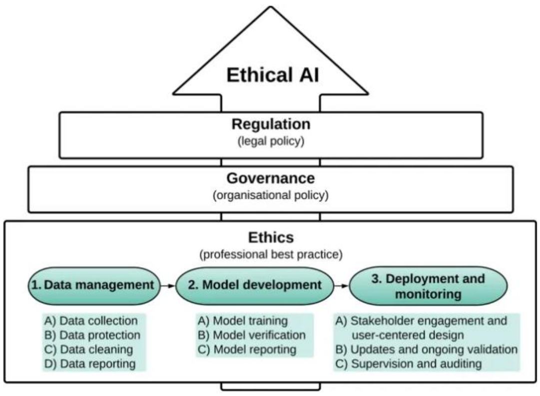

Fig 5: Ethical Considerations in AI and Data Science

8.1. Privacy Concerns

The importance of considering potential privacy concerns when applying the proposed CL-XGBoost to financial information is evident. This includes aiming to keep any sensitive information, e.g., concerning individual financial data, internal organization policies, etc., protected. Using AI algorithms usually requires certain data characteristics such as input variables, data distributions, labels (if applicable), etc. This can cause potentially worrisome privacy concerns. For example, financial information can be highly sensitive. It can even become a matter of national security. Using sensitive data for training AI models may cause suspicion, worrying that these third-party AI service providers can leak this information or analyze them further for other purposes. This, in turn, may also raise legal restrictions on using sensitive information, and implementing those may counteract the benefits of applying AI models.

In the past decade, there has been a growing contribution from academics and stakeholders towards dealing with dataset privacy concerns while preserving the quality of the data for analysis. Privacy-preserving methods of data publishing, clustering and recommendation have been applied to different fields. For example, a recent literature review summarizes existing data publishing techniques such as heuristic methods, encryption-based methods, randomization-based methods, and optimization-based methods. The analytical methods could also be used later on those published data with little privacy concerns. Some have focused on publishing sufficiently large volumes of data under generative models such that aggregated reasoning would still be possible with very little privacy concerns. Privacy policies shall also be stable across the community participants, to block the attacks effectively.

Other studies have elaborated on the association rule hiding methods and the privacy-preserving data mining methods that can tackle them. Game theoretic methods can optimize those trade-offs among participants. Differential privacy could be used for many different types of data mining tasks against many potential quasi-identifiers. Recently, the ability of the differentially private algorithms to withstand de-anonymization attacks while analyzing large tax datasets. Advances such as k-anonymization, t-closeness, generalization, and perturbation-based methods have been applied to relational databases and different application domains such as graph data.

8.2. Bias in Algorithms

Although use of data is a better model of transparency in public finance and budget decisions than the closed-door methods of yesteryear there are several known biases present in data algorithms that undermine the effectiveness and trustworthy nature of the models that use them to make automatically collected analytic decisions. Data-driven algorithms in decision making are increasingly used to make decisions that impact social and economic well-being. These algorithms are often predictive models. There is a growing concern about their potential discriminatory impact. Fair ML is concerned with measuring and mitigating the unfairness inherent in the decisions made automatically through these models. Existing work identifies bias in the decisioning algorithm or the data off which it was trained and evaluated. Dataset bias is often ignored but on its own can account for much discriminatory impact. This class of bias arises from inaccuracies in the data that contribute to the model's inference. In the quest to understand fairness, fairness metrics are proposed to evaluate the impact of dataset bias either directly or indirectly.

With their increasing adoption comes a powerful backlash. Defenders of the status quo decry abuses in auto-adjudication of credit, welfare, and criminality decisions, calling for a moratorium on machine learning in high stakes settings. For every visible injustice—e.g. the auto-refusal of loans to women or of credit cards for black borrowers—new research emerges to argue in favor of machine learning for its high utility, accuracy, and fairness. For every new metric of error discrepancy, new pre-processing interventions emerge to constrain models with respect to those metrics. Policymakers around the world are simultaneously declaring war on the pernicious side of algorithms, while tasking governments to adopt algorithmic systems to combat corruption and inefficiency. For modellers, the challenge now exists of crafting a new class of methods applicable to arbitrarily complex applications—the legacy of the defense and assertion brief.

9. Conclusion

We presented TaxAI, a dynamic economic simulator for policy studies and reinforcement learning applications. It employs the Bewley-Aiyagari model and integrates realistic elements to replicate diverse economic environments. To examine the ability of various fiscal policy design methods, we benchmarked two economic methods and seven RL methods. We hope to bridge the gap between economic theory and AI methods by outlining future research directions.

TaxAI is a flexible simulator with broad applicability. It can embody different kinds of tax, incorporate transfer payments, and model different agent behaviors, such as more complex choices and preferences. It can also investigate other economic problems beyond fiscal policy. Future work will focus on variety and robustness.

Another promising direction is to strengthen the platform for RL methods. Regarding multi-agent design, we may unlock the intricate interaction procedures of agents, allowing adaptive strategies and opinions among household agents. We may also allow agents to learn external primitives, increasing independence. Nevertheless, potential design flaws, such as undesired emergent behaviors, must be addressed.

This research offers ideas for future efforts to improve government fiscal policy settings. Sound fiscal policies are critical for the sustainable development of a nation's economy. Suitable AI and ML methods can provide government departments with applicable analysis and decision-making solutions for their policies. To facilitate discussions and collaborations in this area, we hope TaxAI will stimulate the development of other simulators for large-scale RL studies on fiscal policy.

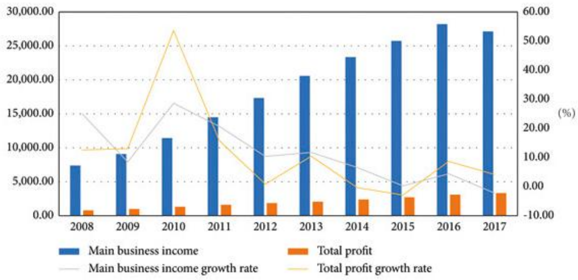

Fig 6: Big Data Model in Financial Taxation Management

9.1. Future Trends

In March 2023, we demonstrated "TaxAI," the first economic simulator dynamic enough to respond to tax law changes in online games. It could be an excellent benchmark for researchers and developers to assess the applicability of AI in fiscal policy problems using multi-agent reinforcement learning (MARL). After introducing the game environment, we forecasted the results of increasing the upper limit of tax brackets on the rich's wealth and devising tax reductions for the poor and middle class on tax revenues using XGBoost. Also, we showed the potential of TaxAI as a benchmark game for performance enhancement. Historical tax policies in TaxAI were trained using a double-ended LSTM model, combined with behavior cloning in real historical game states to optimize agents' performances significantly. The XGBoost-based government agent easily predicted macro re-statistic variables and improved the game results in performance through action masking.

Though advancements have been made, continuous research and applications are required to reduce bias, avoid overfitting models, analyze predictions, and aggregate them in economic policy. Furthermore, the rapid development of AI and machine learning continues to shape how public finance is managed and restructured. AI-based decision-making may increase the incentive for the government to interfere, but the emergence of bias detection tools could counteract those biases. AI is expected to enhance interactions between multi-tier governments, companies, and the population by providing scenarios and forecasts to aid in formulating plans and strengthening cooperation, as well as in conceptions for investments and financing. Natural language processing (NLP) could allow governments to analyze large amounts of textual and time-based data. Government agents could exploit new datasets, such as satellite view data or payment tracking systems.

The rapid increase in big data sources on social problems, alongside their potential cross-border impacts, may enhance the role of global organizations in policy making. AI and big data will play important roles in tracing actions, understanding motives, comparing policies, forecasting results, and evaluating them. The scope of considered problems is likely to be broadened to asymmetric actions' dynamics, multi-agent settings, and issues with greater importance than compliance, like tax fraud or duties imposed under dual use. Also, recent AI developments could enhance analytical efforts in Federal Reserve affairs or regarding key questions in economic theory, like whether losses can be mitigated in boom-to-bust cycles and how deep and politically efficient interventions should be.

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