Simulation Card: Foundation (Economic Simulation Framework)

Last updated: 10/14/2020

Simulation Details

Organization	Salesforce AI Research
Simulation date	August 5, 2020
Simulation version	1.1.1
Citation Details	Zheng, S., Trott, A., Srinivasa, S., Naik, N., Gruesbeck, M., Parkes, D. C., & Socher, R. (2020). The AI Economist: Improving Equality and Productivity with AI-Driven Tax Policies. arXiv preprint arXiv:2004.13332.
Paper	https://arxiv.org/abs/2004.13332
Keywords	Economics, simulation, reinforcement learning
License	BSD3
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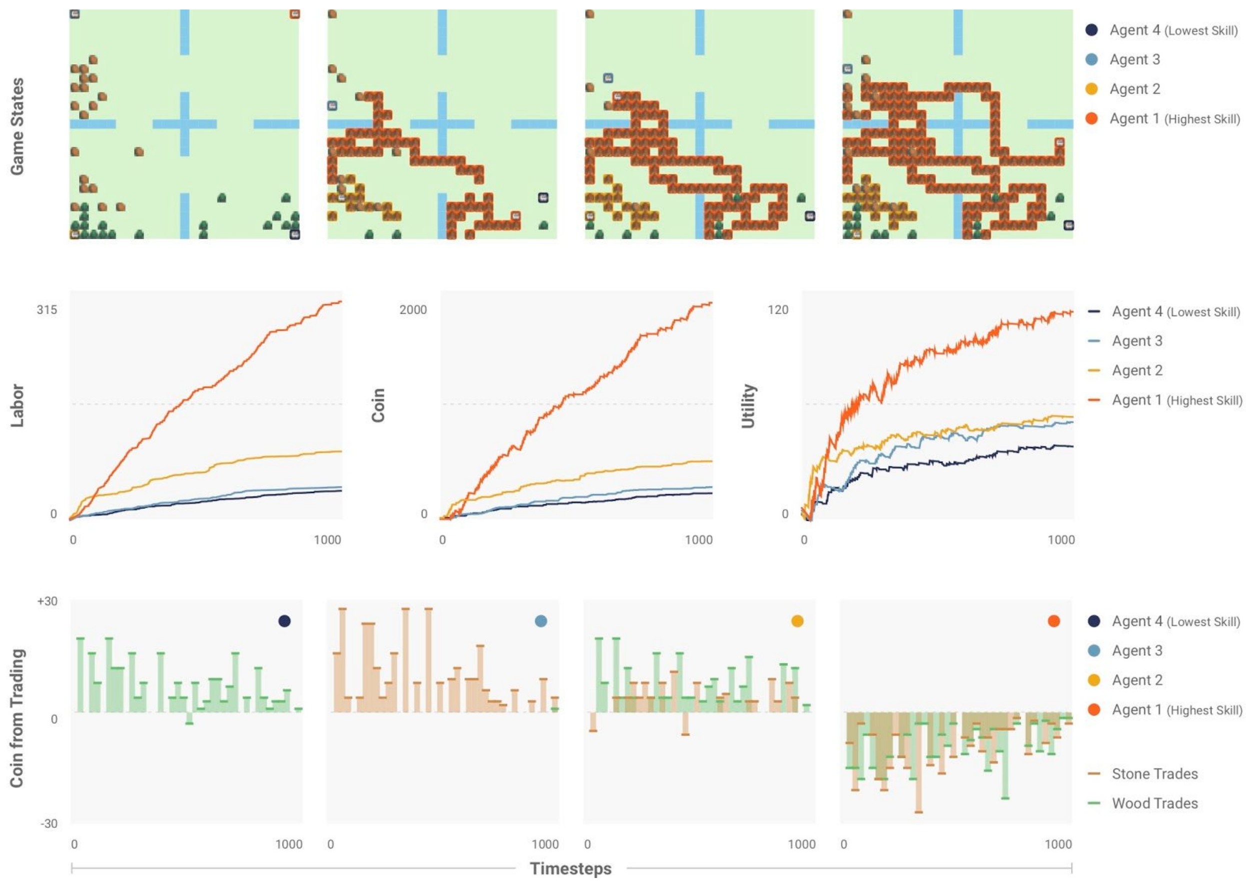
Basic Information

Through the Foundation framework, we're bringing reinforcement learning (RL) to tax research for the first time to provide a data-driven solution for defining optimal taxes for a given socio-economic objective. For this purpose, the Foundation simulates a population of AI agents, who are designed to replicate how real people might react to different taxation schemes.

The main component is a game engine-like simulation tool that generates a physical environment (in the form of a map containing ground and water), material resources (e.g., stone and wood), material rewards (e.g., houses and money), and a population of agents that interact with this environment by collecting and trading resources, building houses, and making money.

The simulation manages various economic processes required for a functioning economy. It regenerates resources when they are depleted. For the agents, it provides processes for gathering resources, trading resources among each other, and building houses by spending gathered resources, and receiving money for the labor of building houses. The simulation also implements rudimentary two-dimensional physics with rules that prevent agents from crossing a stream of water or block each other from accessing resources by building houses.

The agents are endowed with skills for collecting resources and building houses. The skill is sampled from a distribution specified by the human designer. The agents can also have different starting locations and wealth, which can affect their future earnings. There are no other inherent differences between the agents.

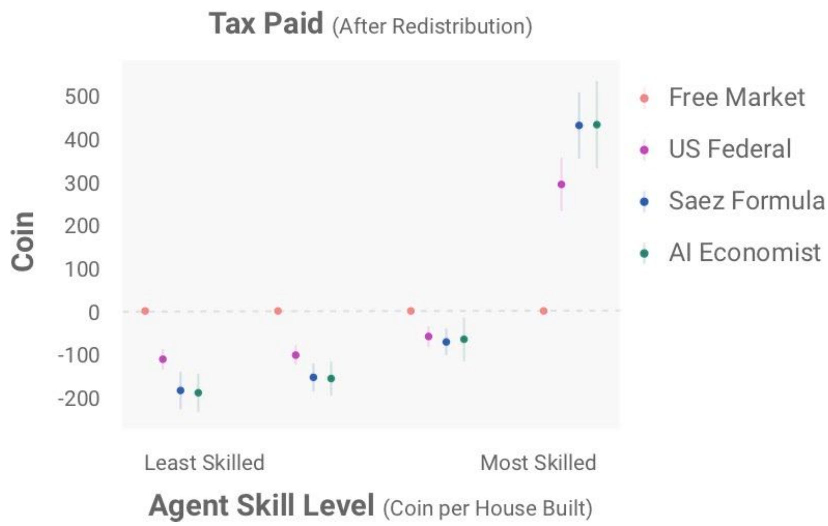


This figure presents a qualitative and quantitative analysis of a simulation rollout. The top plots provide sequential snapshots of the spatial state of the simulation, including resources, agents, and built houses. The middle plots show, for each agent, the cumulative Labor performed, Coin earned, and Utility experienced. The bottom plots show, for each agent, the income/expenditure through trading for each of the 2 resources over the course of the rollout.

Intended Use

The simulation was designed with the primary goal of tax policy design and for studying productivity and equality under various tax policies. Agent behavior under various policies can be studied when the agents are trained using reinforcement learning, or are controlled by human agents. The primary intended users of this simulation are researchers (e.g., computer scientists, economists) and economic policymakers.

The AI Economist (Zheng et al, 2020) used Foundation and reinforcement learning (RL) to train AI agents to maximize their utility by adjusting their movement, trading, and building behavior in the simulation. The AI Economist learns a taxation scheme (that includes income taxes and subsidies) which is applied on the agents to promote global objectives defined by the human designers of the simulation. It also trains the agents to adjust their behavior in response to the taxation scheme, based on their defined utility. All trainable agents of the simulation, including the AI Economist, can be replaced by predefined behavior policies or by humans controlling some/all of the agents. In effect, the AI Economist achieves better social welfare through more effective taxation and redistribution leading to a better trade-off between equality and productivity.



This figure shows the net effect of taxes (the sum of taxes paid and subsidies received) for each agent (left to right) across a variety of tax schemes (color of the dots). This analysis provides insight into the degree of redistribution achieved by each tax scheme.

Factors

The simulation is based on key modeling assumptions that are common in neoclassical economics, which include modeling skills, endowments, and utilities of economic agents. It is not based on observational data or a societal model derived from a particular society.

Metrics

The simulation provides its human designers full control of the metrics used to optimize the agent behaviors and tax policies. Once these metrics are defined, the simulation uses RL to train policy models based on generated data to optimize the metrics. Currently the social metrics include equality and productivity of the agent population. Equality is defined as 1 - Gini-index and productivity is defined as the sum of all agents' incomes in the simulation. The metric for agents is a CRRA utility function to measure their happiness as a function of income and labor.

The performance of the AI Economist is measured by the product of equality and productivity, which captures the idea that optimizing social welfare should include optimizing both equality and productivity simultaneously. Future extensions could include quantifiable metrics for ethical or fair agent and social planner behavior.

In general, RL agents have been shown to be able to find strategies to exploit flaws in the simulation ("reward hacking"). This continues to be an active area of research. In our experiments, economic agents learned strategies to minimize their tax burden, but no egregious reward hacking behavior outside the range of normal economic behavior was observed.

Quantitative Analyses

The simulation allows the user to generate plots and other visualizations on all resources, trades, and material rewards collected by the agents, in addition to data on taxation and derived metrics like labor.

Ethical Considerations

While the simulation cannot be used in a real-world setting today, we recognize that it could be possible to manipulate future, large-scale iterations of the simulation to increase inequality and hide this action behind the results of an AI system. Either out of ignorance or malice, bad training data may result in biased recommendations, particularly in cases where users train the tool using their own data. For instance, the under-representation of communities and segments of the workforce in the training data could lead to bias in AI-driven tax policies. This work also opens up the possibility of using richer, observational data to set individual taxation, an area where we anticipate a strong need for robust debate. We encourage anyone modifying our simulation to design tax policies to publish a simulation card that describes the ethical considerations of AI-driven tax schedules in order to increase transparency, and by extension, trust, in the system. Similarly, we encourage to include a [model card]() or [fact sheet]() for models trained using our simulation.

Caveats and Recommendations

AI-based economic simulations have limitations and should not be used to reconfigure tax policy in the real world today. The simulations do not yet model human-behavioral factors and interactions between people, including social considerations, and they consider a relatively small economy.

However, these kinds of simulations provide a transparent and objective view on the economic consequences of different tax policies. Moreover, this simulation and data-driven approach can be used together with any social objective in order to automatically find a tax policy with strong performance. Future simulations could improve the fidelity of economic agents using real-world data, while advances in large-scale RL and engineering could increase the scope of economic simulations.

More information

- Code: www.github.com/salesforce/ai-economist
- Tutorials: www.github.com/salesforce/ai-economist/tutorials
- General information: www.einstein.ai/the-ai-economist
- Paper: Zheng et al, 2020: https://arxiv.org/abs/2004.13332
- Blog: https://blog.einstein.ai/the-ai-economist
- Moonshot Announcement: https://blog.einstein.ai/the-ai-economist-moonshot