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Comments on

Estimating Policy Functions in Payments Systems Using Reinforcement Learning

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Disclaimer: The opinions expressed here do not represent the views of CEMLA.

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Summary of the paper

- The paper is very interesting with **innovative methodology**. Reinforcement Learning (**RL**) could promote the proper functioning of the Payment Systems (PS).

- **Large-value payment systems** (LVPS) generally settle in real-time. Banks choose the amount of **liquidity** provided to the payment systems
  - Given the costs of liquidity, banks and regulators fine tune their policy functions.

- **Authors suggest** a model with **two agents** who **optimize liquidity** using **RL** and learn an **optimal policy**
  - That minimizes the cost of processing their individual payments.
  - Yet, a more realistic LVPS would involve multiple participants and periods.

- **The estimation of a policy function for LVPS using RL** is then **motivated** by:

  1) **Assisting policy-makers** and payment system **participants** to define optimal initial liquidity at the lowest cost.

  2) **Designing new payment systems**.

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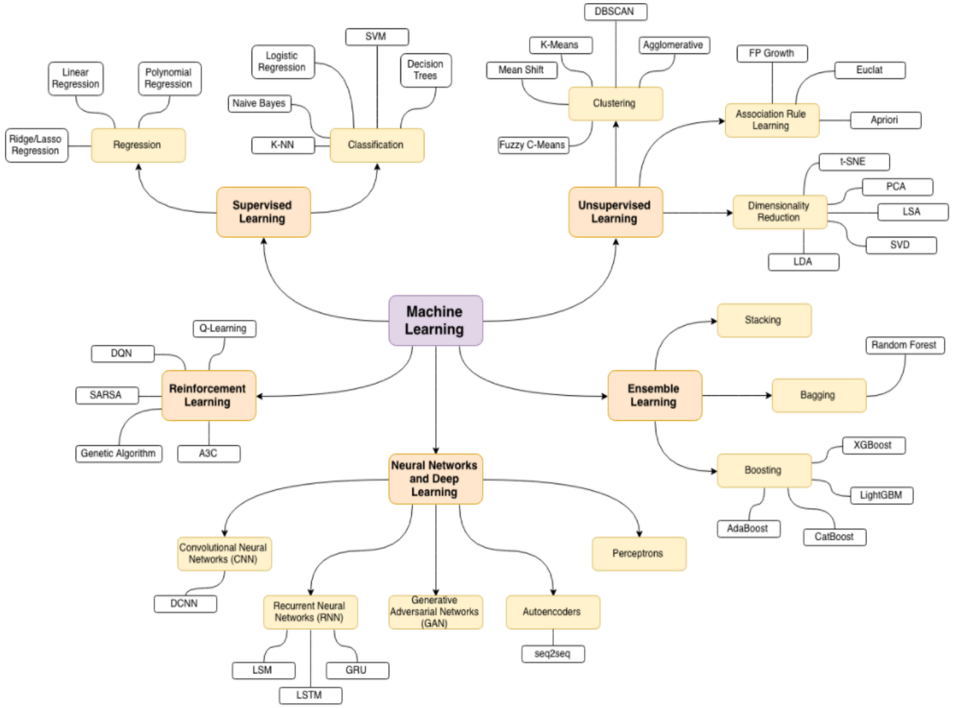
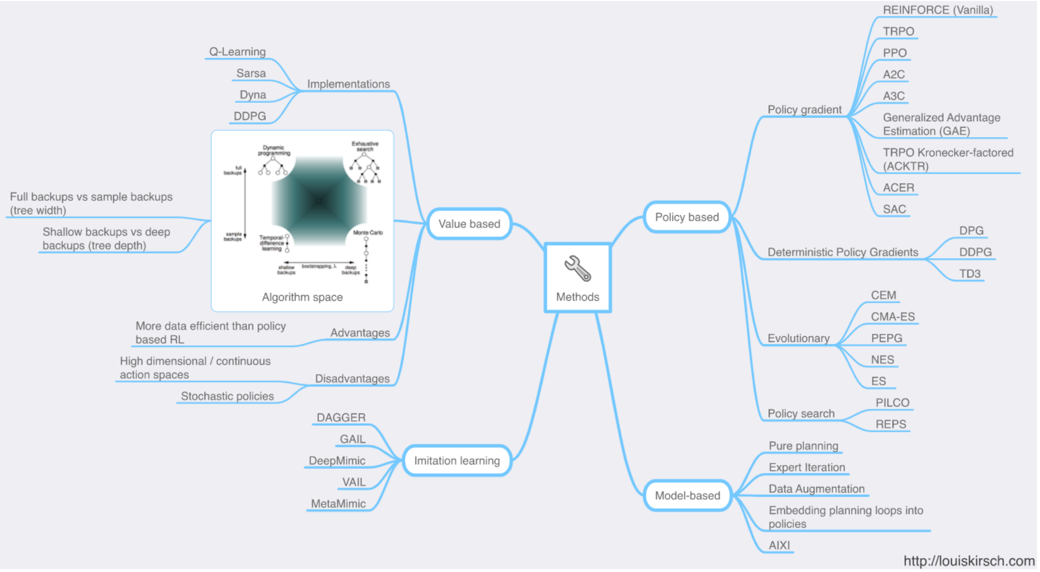
Comments

- What other **Machine Learning (ML)** techniques did you consider to estimate this issue?
- For training you used the REINFORCE algorithm (*policy gradient technique*). There are a variety of **methods to optimize an agent's policy,** even within RL, including:
  - *Deterministic Policy Gradients*
  - *Evolutionary*
  - *Policy search*
  - **Model based**
  - **Imitation learning**
- Why did you choose RL-REINFORCE?



Source: https://github.com/trekhleb/homemade-machine-learning



Have you thought for your **future research work** to estimate more than two agents and periods with **other ML techniques**?

Comments

- Overall comments
  - The **applied game theory** literature is one of their contributions, as it is the starting point for the **RL exercise**. Prior work is the theoretical model of Bech and Garratt (2003).
    - Works related to RL: Roth and Erev (1995), Fudenberg and Levine (2016), among others.
  - The **authors acknowledge** that:
    - **Their model** of the environment abstracts from **two important dimensions of PS**:
      - The **indivisibility of payments** and
      - The **interbank liquidity market**.
- On the methodology
  - The **RL agent learns** about their own environment. RL guides the participant behavior.
  - Limitations of the **RL** models are the *non-analytic solutions*, but a **simulation-based optimization** is provided.
  - It is important to have estimates of the sensitivity of the agent's best responses, at different levels of delay cost.
    - Because delay cost is unobservable to researchers and policy-makers.
    - How cost could be misleading without an interbank market?

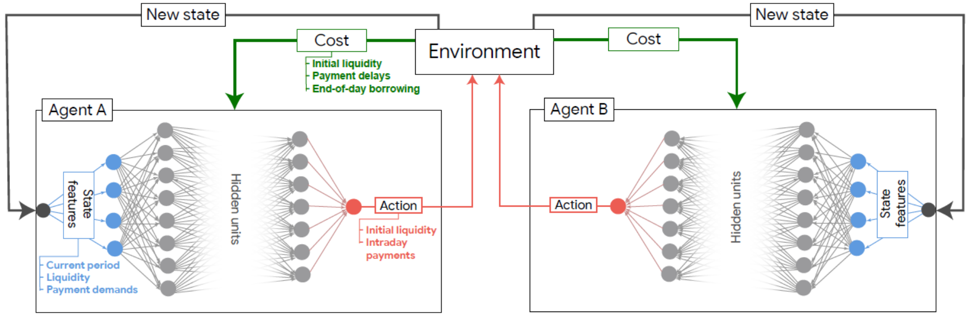
Future work

We are curious to see your future work on:

- How would **agents behave** if they were knowing the **initial liquidity** and the **inter-day payment**, at the same time?

- Introduction of **some realistic features** of the payment system
  - Modeling more than two agents, a more **complex scenario**.
  - Non-divisible payments.
  - Considering (cheaper) interbank market liquidity.

Current paper. Figure 2: Reinforcement Learning in the context of a payments system, two banks (agents)



Source:Castro, P. S., Desai, A., Du, H., Garratt, R., & Rivadeneyra, F. (2020). Estimating Policy Functions in Payment Systems using Reinforcement Learning. *Available at SSRN*.

Thinking of **hybrid LVPS**, how useful is this approach to design **liquidity policy functions** for (retail) **fast payment systems**? This could be a research extension.

Great and exciting fields to be explored!

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Thank you!

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