

Research Statement

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As a Reinforcement Learning (RL) researcher working closely with researchers in control theory, game theory, and language models, I design, analyze, and evaluate algorithms that achieve optimality with fewer interactions and information from environments. Our algorithms combine insights from standard model-based control with the adaptability of black-box learning methods to effectively model complex environments. These algorithms are also applicable to multi-agent systems involving human participants, where humans are treated as black-box agents while other agents follow a model-based approach. (Fig. 1)

In my doctoral research at University of Illinois Chicago, I have applied *model-based reinforcement learning*, *switched control theory*, *stochastic game theory*, and *composite optimization* to develop algorithms that leverage model information to accelerate model-free training, achieving greater sample efficiency. The algorithms designed require fewer interactions with the environment to achieve the same level of optimality (Fig. 2). Additionally, we extended the algorithm to multi-agent systems involving both human (model-free) and AI (model-based) agents, enabling effective collaboration between the AI and human agents without the need to control or model human behavior (Fig. 3 and Fig. 4).

Beyond these researches, which I correspond to, I am also interested in LLMs in decision-making. Together with researchers at Stony Brook University, we developed a hybrid system for end-to-end autonomous driving¹, integrating Large Language Models (LLMs) as high-level instructors to enhance the generalization capabilities of local end-to-end models. Our approach mitigates the latency impact of LLMs and is the first to apply LLMs to real-world, closed-loop, end-to-end autonomous driving (Fig. 5).

I am now exploring ways to generalize these methods beyond toy experiments to help data scientists, automotive engineers, journalists, and other end-users more easily train AI agents for deployment in real-world environments, such as autonomous driving, industrial robotics, AI for science, and healthcare.

Beyond research in academia, I am a co-founder of LIII NETWORK, an open-source company that developed GNU $\text{\TeX}_{\text{MACS}}$ /Mogan, a WYSIWYG \TeX -like editor enabling users to type equations 10 times faster—and Goldfish Scheme, a Scheme interpreter with a Python-like standard library. Goldfish Scheme is developed using literate programming, a methodology introduced by Knuth in 1984, which we believe will gain renewed relevance in the era of LLMs.

1. Combining model-based control and model-free learning

Many real-world nonlinear systems are challenging to model accurately. While linear approximation models simplify this process, they introduce model bias that can lead to highly suboptimal policies if used exclusively in model-based control. On the other hand, model-free methods require substantial data to

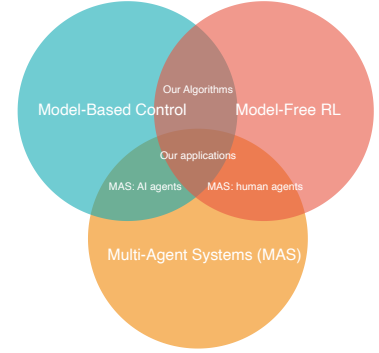


Figure 1: Model-based control and model-free reinforcement learning

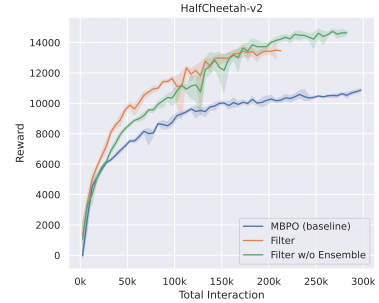


Figure 2: Filter and Filter w/o Ensemble are our algorithms



Figure 3: Green: AI agents; Blue: Human agents. Initial position.



Figure 4: The AI agent successfully changed the lane.

¹ Z. Dong, Y. Zhu, **Yansong Li**, K. Mahon, and Y. Sun*. Generalizing end-to-end autonomous driving in real-world environments using zero-shot LLMs. In *8th Annual Conference on Robot Learning*, 2024. URL <https://openreview.net/forum?id=s0vHSq5QE>

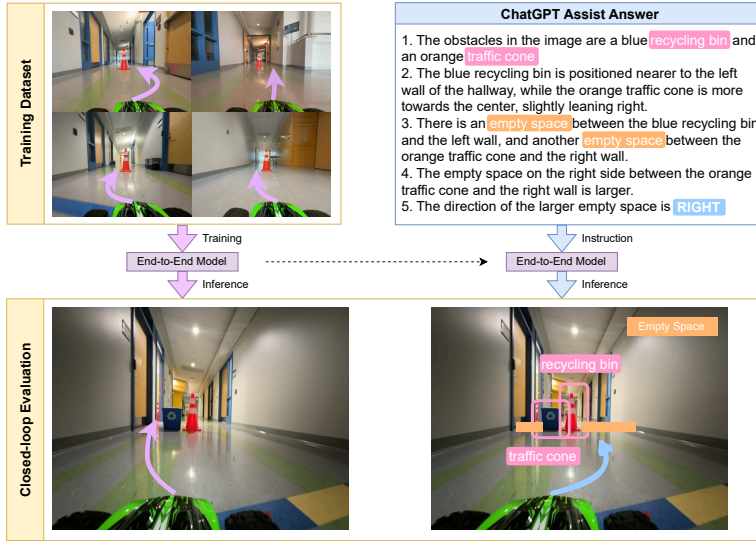


Figure 5: LLMs enhances the generalization of autonomous driving.

learn an optimal policy, which can be impractical for physical systems. To address this issue, we developed several hybrid algorithms based on composite optimization and Dyna-style learning, which integrates model-based control using approximation models with model-free methods, requiring less data to achieve the same level of optimality as purely model-free approaches.

GRADIENT COMPENSATION (GC) algorithm is a switched algorithm developed based on composite optimization, which integrates model-based control using linear approximation models with model-free methods, requiring less data to achieve the same level of optimality as purely model-free approaches.²

- GC algorithm: $\nabla \hat{f} \xrightarrow{\nabla \hat{f}=0} \nabla f \rightarrow \tilde{g}^{(1)} \xrightarrow{\text{LSF}} \nabla f \rightarrow \tilde{g}^{(2)} \xrightarrow{\text{LSF}} \dots$

We build a switching rule LSF that switches between the model-free gradient ∇f and the gradient \tilde{g} computed from the linear estimated model. The \tilde{g} is updated whenever a model-free gradient ∇f is called.

Societal and potentially commercial impact

Algorithms that combine model-based control with model-free learning methods are well-suited for application in complex, real-world environments. First, these algorithms require fewer interactions with the environment during training, making deployment more cost-effective and safer. Second, the model-based components offer interpretability, allowing for a clearer understanding of the AI agent's behavior and easier modification as needed. In the following sections, we list two applications for our algorithms in simulation environments.

Application: Continuous control on legged robots

We developed a *Dyna-style learning with data filter* algorithm³, an extension of Dyna-style learning, which uses data generated from an estimated model to accelerate model-free training. Our modification introduces a filter that excludes data points likely to hinder rather than enhance training speed due to biases in the model's estimations. The algorithm was tested in the Mu-

² Yansong Li* and S. Han. Accelerating model-free policy optimization using model-based gradient: A composite optimization perspective. In R. Firoozi, N. Mehr, E. Yel, R. Antonova, J. Bohg, M. Schwager, and M. J. Kochenderfer, editors, *Learning for Dynamics and Control Conference, L4DC 2022, 23-24 June 2022, Stanford University, Stanford, CA, USA*, volume 168 of *Proceedings of Machine Learning Research*, pages 304–315. PMLR, 2022. URL <https://proceedings.mlr.press/v168/li22a.html>

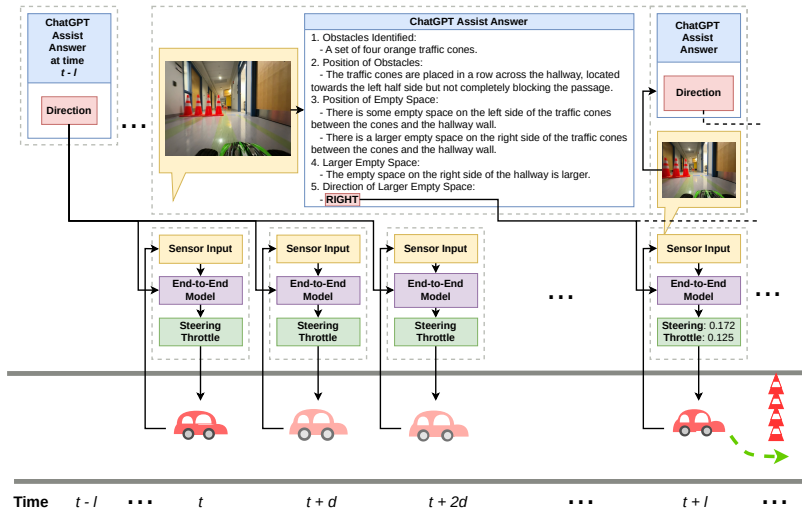
³ Yansong Li*†, Z. Dong†, E. Luo, Y. Wu, S. Wu, and S. Han. When to trust your data: Enhancing dyna-style model-based reinforcement learning with data filter, 2024. URL <https://arxiv.org/abs/2410.12160>

JoCo simulation environment, a platform for legged robot simulations. Our method demonstrates state-of-the-art (SOTA) performance in the model-based RL community, achieving comparable scores with fewer interactions (Fig. 2).

Application: Multi-Agent Systems with Humans In a multi-agent system involving human agents, it can be challenging or impractical to model human behaviors using utility or transition models. One way to address this limitation is to treat human agents as black boxes, observing their actions without assuming a specific model—essentially treating them as model-free components within the system. Conversely, AI agents, which we aim to control, can be modeled explicitly and treated as model-based components within the multi-agent system. Based on this intuition, we developed an algorithm ⁴ for Stackelberg games in normal form that can effectively train an AI agent to collaborate with the follower (human agent) without modeling him. The work is then extended to stochastic games with tabular setting ⁵.

2. Large language models for decision making

As shown in Fig. 5, we developed a hybrid system comprising LLMs for end-to-end autonomous driving. Unlike previous approaches, ours is the first to apply LLMs for closed-loop real-world driving, as illustrated in Fig. 6. Previous work was unable to achieve closed-loop functionality in real-world environments due to the high latency of LLMs to give a direct control signal. We address this challenge by decoupling the LLM model from direct action controls and creating an architecture that integrates multimodal LLMs with end-to-end autonomous driving. The idea behind this setting is our belief that LLMs are not suitable for direct control-level decision-making; however, they can assist decision-making by providing higher-level instructions. We evaluate the effectiveness of the proposed method in a closed-loop, real-world setting. The experiments show that LLMs enhance the generalization of the learning car, enabling it to drive in environments not encountered in the training set. ⁶



⁴ Yansong Li* and S. Han. Solving strongly convex and smooth stackelberg games without modeling the follower. In *American Control Conference, ACC 2023, San Diego, CA, USA, May 31 - June 2, 2023*, pages 2332–2337. IEEE, 2023. DOI: 10.23919/ACC55779.2023.10156010. URL <https://doi.org/10.23919/ACC55779.2023.10156010>

⁵ Yansong Li* and S. Han. Efficient collaboration with unknown agents: Ignoring similar agents without checking similarity. In M. Dastani, J. S. Sichman, N. Alechina, and V. Dignum, editors, *Proceedings of the 23rd International Conference on Autonomous Agents and Multiagent Systems, AAMAS 2024, Auckland, New Zealand, May 6-10, 2024*, pages 2363–2365. International Foundation for Autonomous Agents and Multiagent Systems / ACM, 2024. DOI: 10.5555/3635637.3663161. URL <https://dl.acm.org/doi/10.5555/3635637.3663161>

⁶ Z. Dong, Y. Zhu, Yansong Li, K. Mahon, and Y. Sun*. Generalizing end-to-end autonomous driving in real-world environments using zero-shot LLMs. In *8th Annual Conference on Robot Learning, 2024*. URL <https://openreview.net/forum?id=s0vHSq5QEw>

Figure 6: A closed-loop pipeline of the proposed hybrid system using ChatGPT-4o.

3. Large language models for literate programming

Goldfish Scheme

GNU $\text{T}_{\text{E}}\text{X}_{\text{MACS}}$ is a WYSIWYG $\text{T}_{\text{E}}\text{X}$ -like editor that can help the user type equations 10 times faster than $\text{L}^{\text{A}}\text{T}_{\text{E}}\text{X}$. However, GNU $\text{T}_{\text{E}}\text{X}_{\text{MACS}}$ has several issues, which led us to create a fork called Mogan Research, aimed at addressing these problems and enhancing the user experience. Table 1 provides a comparison.

	GNU $\text{T}_{\text{E}}\text{X}_{\text{MACS}}$	Mogan Research
Release Cycle	not fixed	monthly
Performance	slow	fast
UI Style	retro style	modern style
Shortcuts	some of them do not work	99% of them work fine
Qt Framework	mainly in Qt 4 (some in Qt 5)	mainly in Qt 6 (some in Qt 5)
Scheme Engine	GNU Guile 1.8.x	S7 Scheme
Code Repository	SVN (Savannah)	Git (Codeberg/Gitee/Github)
Build Tool	GNU Autotools	xmake
Lead by	Joris van der Hoeven (Mathematician)	LIII NETWORK

Table 1: Comparison between GNU $\text{T}_{\text{E}}\text{X}_{\text{MACS}}$ and Mogan Research

Goldfish Scheme and literate programming

As shown in Table 1, the Scheme engine for $\text{T}_{\text{E}}\text{X}_{\text{MACS}}$ is GNU Guile 1.8.x, which is no longer maintained by the GNU community. Consequently, the $\text{T}_{\text{E}}\text{X}_{\text{MACS}}$ community decided to maintain their own Scheme interpreter. In contrast, Mogan uses the S7 Scheme as its foundation. However, the S7 Scheme also has limitations, such as incomplete support for R7RS and Unicode. To address these issues, we developed a new Scheme interpreter called Goldfish Scheme, based on the S7 Scheme. Goldfish Scheme is developed using a literacy programming method, first introduced by Knuth in 1984. Literate programming is a method where project code and its descriptions are written together in a single document. Code is presented in interconnected chunks, forming a narrative thread. A utility program then assembles these chunks into executable code, creating a structure that reads as a monologue and, at times, a dialogue. Mogan gives the utility program as a plugin. The literate programming document for Goldfish is available in <https://github.com/LiiiLabs/goldfish/releases/tag/v17.10.9>⁷

Literate programming in the era of LLMs

We believe that literate programming will revive in the era of LLMs. Our conjecture is that projects developed using literate programming are inherently more understandable for LLMs than projects containing even the most detailed comments. To illustrate, we present an example contrasting code with detailed comments and code written in the style of literate programming. As discussed in Section J of ⁸, literate programming enables a flexible structure where code is organized as a "web" of interconnected ideas rather than following a strict top-down or bottom-up sequence. Fig. 7 illustrates this concept with two files connected by ideas. The file `old_packages/sum.scm` contains the original sum function in Scheme, which only accepts integer inputs. The file `new_packages/sum.scm` extends this sum function to accept rational numbers. These two files are linked by ideas rather than function calls or class inheritance. Fig. 7 demonstrates how LLMs can directly recognize these connections, as literate programming allows these chunks to be organized this way. In contrast, Fig. 8 shows the same project with detailed comments. Even with such

⁷D. Shen*, N. Liu[†], **Yansong Li[†]**, D. Wang, L. He, and Y. Zhou. *Goldfish Scheme: A Scheme Interpreter with Python-Like Standard Library*. LIII NETWORK, 2024

⁸D. E. Knuth. Literate programming. *Comput. J.*, 27(2):97–111, May 1984. ISSN 0010-4620. DOI: 10.1093/comjnl/27.2.97. URL <https://doi.org/10.1093/comjnl/27.2.97>

comments, LLMs must read and interpret the paths mentioned within, locate the referenced file, and then analyze it to grasp the connection.

[This is the original scheme sum function, which can only take integers as inputs

```
old_packages/sum.scm
;;This is the original scheme sum function, which can only take integers as inputs
(define (add int1 int2) (+ int1 int2))
```

The new sum function we defined can add two rational numbers.

```
new_packages/sum.scm
;; The new sum function we defined can add two rational numbers.
;; The old sum is defined in old_packages/sum.scm

; Extend the + operator to handle both integers and rationals
(define (extended+ x y)
  (cond
    ((and (pair? x) (pair? y)) (add-rat x y)) ; If both are rationals, add as rationals
    ((pair? x) (add-rat x (make-rat y 1))) ; If x is rational, convert y to rational and add
    ((pair? y) (add-rat (make-rat x 1) y)) ; If y is rational, convert x to rational and add
    (else (+ x y)))) ; Otherwise, use standard integer addition

; Redefine add to use extended+
(define (add rat1 rat2)
  (extended+ rat1 rat2))
```

Figure 7: Two idea-connected files edited in Mogan using literate programming; LLMs can directly read the connection.

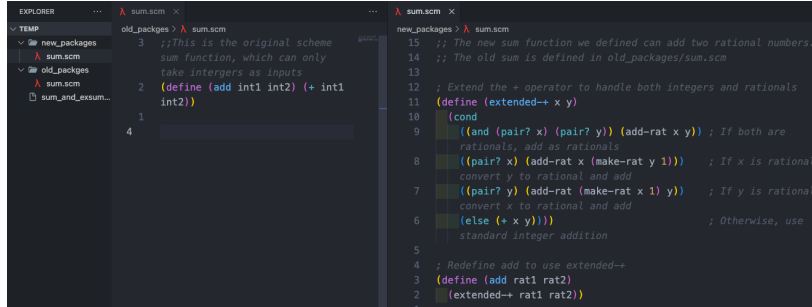


Figure 8: Connection between these two files are commented in new_packages/sum.scm. Even with such comments, LLMs must read and interpret the paths mentioned within, locate the referenced file, and then analyze it to grasp the connection.

Research directions

How can we deploy learning-based decision-making policies in real-world real-time?

Deploying learning-based decision-making policies in real-world real-time faces the following challenges:

- **Data requirements:** Training learning-based policies requires a large amount of data from interactions with the real world. Additionally, training in a simulation environment introduces sim2real challenges, where policies trained in simulation may not perform well when deployed in the real world due to discrepancies between simulated and real-world dynamics.
- **Real-time performance:** Ensuring real-time performance is challenging, as many learning-based policies involve complex computations that may not meet the time constraints required for real-world decision-making.
- **Adaptability to environmental changes:** Handling unexpected environmental changes requires policies to adapt dynamically. Many learning-

based models struggle to generalize to novel situations that were not part of the training data, limiting their robustness in real-world deployment.

Hybrid systems, such as algorithms that combine model-based control with model-free learning, address issues related to data requirements, while the LLM-assisted driving framework⁹ we developed tackles challenges in real-time performance and adaptability to environmental changes. However, beyond the two problems mentioned above, several other challenges have not been addressed in my Ph.D. research, such as:

- **Exploration vs. exploitation balance:** Balancing exploration and exploitation is difficult in real-time applications, as exploration could lead to suboptimal or unsafe decisions, while exploitation may cause the policy to miss adapting to new information.
- **Safety and stability:** Ensuring safety and stability during learning and decision-making is crucial, particularly in high-stakes environments such as autonomous driving or robotic surgery, where incorrect decisions can have significant consequences.

I will continue collaborating with researchers in robotics, control theory, and game theory to further explore these topics and integrate them with my previous research, aiming to develop a more robust AI agent adaptable to real-world applications.

Can LLMs help for decision-making in the real world?

We believe that LLMs can assist in decision-making rather than making decisions directly for several reasons:

- **High Latency:** LLMs require substantial computational power for inference, resulting in latency that can slow down real-time decision-making processes.
- **Limited Context Awareness:** LLMs often lack full awareness of real-time context or situational changes, which can lead to suboptimal decisions if used directly in dynamic environments.
- **Reliability Concerns:** Directly relying on LLMs for decision-making can introduce unpredictable behavior, as they may produce varied responses based on slight changes in input, making them less reliable for critical decisions.

To enable LLMs to assist in decision-making, the design of hybrid systems is essential. I will collaborate with other researchers to explore this topic further.

Renaissance of Literate Programming in the Era of LLMs

As discussed in Section 3, we believe that Literate Programming will revive in the era of LLMs. This falls into a research area called “prompt engineering”. The motivation behind developing Goldfish Scheme for literate programming and prompt engineering experiments includes:

- **Simplicity for Inference:** The Scheme’s minimalistic design limits the options for inference, allowing LLMs to provide more precise and straightforward answers.

⁹ Z. Dong, Y. Zhu, **Yansong Li**, K. Mahon, and Y. Sun*. Generalizing end-to-end autonomous driving in real-world environments using zero-shot LLMs. In *8th Annual Conference on Robot Learning*, 2024. URL <https://openreview.net/forum?id=s0vHSq5QEv>

- **Python Compatibility for Knowledge Transfer:** LLMs are generally more familiar with Python due to extensive training in Python code. Since the Goldfish Scheme includes several features from Python's standard library, it enables smoother knowledge transfer from Python to the Goldfish Scheme, making it more accessible for LLMs than other Scheme variants.

However, literate programming faces several challenges, such as difficulties with collaboration, version control, and establishing clear writing standards, which are harder to define than coding standards. Together with my colleagues at LIII NETWORK, we will continue exploring the potential of literate programming and LLMs to address these challenges.

References

- Z. Dong, Y. Zhu, **Yansong Li**, K. Mahon, and Y. Sun*. Generalizing end-to-end autonomous driving in real-world environments using zero-shot LLMs. In *8th Annual Conference on Robot Learning*, 2024. URL <https://openreview.net/forum?id=s0vHSq5QEY>.
- D. E. Knuth. Literate programming. *Comput. J.*, 27(2):97–111, May 1984. ISSN 0010-4620. DOI: 10.1093/comjnl/27.2.97. URL <https://doi.org/10.1093/comjnl/27.2.97>.
- D. Shen*, N. Liu[†], **Yansong Li**[†], D. Wang, L. He, and Y. Zhou. *Goldfish Scheme: A Scheme Interpreter with Python-Like Standard Library*. LIII NETWORK, 2024.
- Yansong Li*** and S. Han. Accelerating model-free policy optimization using model-based gradient: A composite optimization perspective. In R. Firoozi, N. Mehr, E. Yel, R. Antonova, J. Bohg, M. Schwager, and M. J. Kochenderfer, editors, *Learning for Dynamics and Control Conference, L4DC 2022, 23-24 June 2022, Stanford University, Stanford, CA, USA*, volume 168 of *Proceedings of Machine Learning Research*, pages 304–315. PMLR, 2022. URL <https://proceedings.mlr.press/v168/li22a.html>.
- Yansong Li*** and S. Han. Solving strongly convex and smooth stackelberg games without modeling the follower. In *American Control Conference, ACC 2023, San Diego, CA, USA, May 31 - June 2, 2023*, pages 2332–2337. IEEE, 2023. DOI: 10.23919/ACC55779.2023.10156010. URL <https://doi.org/10.23919/ACC55779.2023.10156010>.
- Yansong Li*** and S. Han. Efficient collaboration with unknown agents: Ignoring similar agents without checking similarity. In M. Dastani, J. S. Sichman, N. Alechina, and V. Dignum, editors, *Proceedings of the 23rd International Conference on Autonomous Agents and Multiagent Systems, AAMAS 2024, Auckland, New Zealand, May 6-10, 2024*, pages 2363–2365. International Foundation for Autonomous Agents and Multiagent Systems / ACM, 2024. DOI: 10.5555/3635637.3663161. URL <https://dl.acm.org/doi/10.5555/3635637.3663161>.
- Yansong Li***[†], Z. Dong[†], E. Luo, Y. Wu, S. Wu, and S. Han. When to trust your data: Enhancing dyna-style model-based reinforcement learning with data filter, 2024. URL <https://arxiv.org/abs/2410.12160>.