Personal Statement

Application to the PhD Program, College of Artificial Intelligence, Tsinghua University

The pursuit of intelligence has always seemed to me a question not merely of algorithms, but of **form**—of how structure gives rise to reasoning, and how systems learn to compose ideas in ways that transcend their parts. While recent advances in artificial intelligence have demonstrated the power of scale, my research interests are guided by the conviction that robust reasoning and systematic generalization emerge from the **internal organization of representations, shaped by structural inductive biases**. In particular, I am motivated by the study of how compositional, relational, and geometric structure can be embedded into learned representations so that reasoning arises as a consequence of form, rather than as an accidental byproduct of data.

My academic background is rooted in quantitative and mathematical training, including formal study in **financial mathematics**, which has shaped how I approach problems in artificial intelligence. Early exposure to probability theory, stochastic processes, optimization, and mathematical modeling cultivated a strong sensitivity to abstraction and internal structure. Working with complex, high-dimensional systems governed by uncertainty reinforced the importance of principled representations and invariants—perspectives that naturally carried over into machine learning research. Rather than viewing AI as a departure from mathematical reasoning, I see it as a continuation—one that demands both formal insight and empirical grounding.

During my Master's research, culminating in my thesis *On Why Form Shapes Reason*, I focused on models designed to perform structured transformations and compositional reasoning. Through hands-on experimentation, I observed that models trained primarily through data-driven objectives often succeed at interpolation, yet struggle with systematic recombination. These experiences reinforced my belief that **explicit structural biases**—rather than implicit statistical correlations alone—are necessary to support reasoning that generalizes beyond observed configurations. Importantly, this work involved not only theoretical formulation but also extensive model implementation and empirical evaluation, including ablation and benchmarking on reasoning tasks.

In parallel with this work, I explored reasoning from a complementary methodological perspective through research on **agentic reasoning systems** and **double machine learning for causal inference**. In my work on agentic reasoning, I investigated modular, state-driven architectures in which multiple language-model-based agents interact through structured routing, uncertainty assessment, and hierarchical control. This approach reframes reasoning not as a monolithic forward pass, but as an emergent process arising from coordination, persistence, and selective refinement across agents. Separately, through work on double machine learning, I studied how **orthogonalization and structural constraints** enable reliable causal reasoning in high-dimensional settings, where naïve predictive learning fails to distinguish correlation from causation. Together, these experiences reinforced a unifying insight: **robust reasoning depends less on scale alone than on the explicit structure imposed on representations, interactions, and inference pathways**.

This line of work profoundly shaped how I view intelligence. It convinced me that reasoning is not an add-on to perception, but a property of structure—that the form of representation determines the generality of behavior. It also brought me closer to the philosophical roots of machine learning: the view that learning systems should not be designed merely to memorize solutions, but to discover the invariants underlying those solutions. This pursuit of invariant structure, of geometry beneath generalization, is what ultimately motivates my desire to continue this line of inquiry at the Ph.D. level. Across both natural and artificial systems, intelligence emerges when information attains structure—from biological codes to formal mathematical descriptions—for it is within such organization that reasoning takes shape.

I am applying to **Tsinghua University's College of Artificial Intelligence** because of its distinctive emphasis on foundational AI research that integrates theory and empirical modeling. The College's interdisciplinary environment, which brings together perspectives from machine learning, representation learning, and cognitively inspired approaches, offers an ideal setting for the type of research I seek to pursue. Tsinghua's commitment to long-horizon scientific questions, alongside its strong culture of technical rigor, aligns closely with my interest in understanding the principles that underlie intelligent behavior, rather than optimizing for short-term performance metrics, particularly in representation learning and reasoning.

Within this environment, I am particularly interested in working under **Prof. Yue Song**, whose research on structured representation learning closely aligns with my intellectual orientation. Prof. Song's focus on representations that encode relational and compositional regularities resonates strongly with my own efforts to understand how reasoning emerges from internal structure. Beyond topical alignment, I am drawn to a shared research philosophy: that progress in artificial intelligence requires principled constraints on representation, informed by structure rather than imposed heuristics.

During my postgraduate study, my primary objective is to develop into an independent researcher capable of framing and pursuing foundational questions in artificial intelligence. This includes deepening my theoretical grounding, refining my ability to design models with explicit inductive structure, and learning to evaluate such models in a principled and systematic manner.

After completing the PhD, I intend to pursue a research-focused career centered on the development and application of foundational AI methods, particularly in environments that allow close interaction between theory, experimentation, and real-world systems. I am especially interested in settings where ideas about representation, reasoning, and structure can be translated into robust, usable frameworks that inform the design of intelligent systems. My long-term goal is to contribute research that not only advances understanding, but also shapes how reasoning-oriented models are built and deployed in practice.

Ultimately, I am motivated by a simple but ambitious question: **what properties of learned representations are required to support reasoning and generalization?** I view this question as central to the broader goal of understanding systems that learn, adapt, and generalize across both natural and artificial domains. My long-term research interest lies in investigating how such emergence can be guided by the interaction between **structural inductive biases** and learning dynamics. In essence, my motivation for pursuing doctoral study is to contribute to the foundations of learning—to study not only how machines can reason, but how reasoning itself arises from the structure that learning discovers. I hope to pursue this inquiry with a spirit of rigor and imagination, seeking principles by which form shapes reason.