Pretrained language models (LMs) with billions of parameters increasingly function as general-purpose NLP systems, often outperforming task-specific models, even without fine-tuning. However, they have unexpected failure modes and are notoriously difficult to control. I am excited about developing tools for understanding and responsibly developing general-purpose LMs. For instance, knowing how LMs learn from context can guide us toward better techniques for controlling them via natural language, and testing LMs' susceptibility to adversarial attacks can the spur progress toward safer NLP. As an undergraduate computational linguistics researcher at Harvard (advised by Stuart Shieber and Yonatan Belinkov) and subsequently as a pre-doctoral researcher at AI2 (advised by Peter Clark and Ashish Sabharwal) I have cultivated a multi-perspective approach to understanding and using LMs. I aim to build on this during my PhD by drawing on fields such as syntax and formal language theory to create practical and theoretical frameworks towards **understanding, evaluating, and safely using** LMs as **general-purpose NLP systems.**

Understanding and improving LMs through linguistics Modern NLP is largely divorced from our understanding of linguistics. I am interested in reconciling these to lend clarity to how LMs work, which is a first step towards improving them. For instance, I investigated how modern LMs handle syntactic agreement in my first-author ACL 2021 paper [1] where we intervene on neurons in transformers to observe their causal effect. We find, among other things, that transformers learn two distinct mechanisms for number agreement, and that these mechanisms are distributed in the activations of the network, rather than concentrated in any single model component. These findings elucidate how LMs mimic syntactic behavior, and subsequent research has built on our work to interpret other linguistic phenomena such as distributivity [2]. In future research, I hope to explore linguistically informed approaches that improve LM capabilities. For example, I am interested in leveraging research on linguistic change to enable LMs to adapt to new linguistic patterns. This might be achieved by pretraining on augmented data that randomly introduces hypothetical but plausible linguistic changes, forcing the model to learn how to generalize effectively. Success would result in LMs that can adapt to language it has not seen in training.

Understanding LMs through formal languages I am excited by projects that borrow from formal language theory to increase our understanding of LMs. This approach enables answering questions that we cannot study via natural language. For instance, I used regular languages to **measure the capabilities of transformers as instruction followers** in RegSet, my first-author EMNLP 2022 paper [3]. Large, pretrained LMs solve some NLP tasks by conditioning their generations on natural language instructions for the task [4, 5]. On the other hand, LMs often struggle with compositional generalization [6]. This bodes poorly for the instruction following regime where the space of instructions is highly compositional. Moreover, natural language fuzziness complicates predicting which instructions are challenging for transformers. In response, we propose a proxy for instruction learning by studying instructions in the form of regular expressions. We test the effects of regular language attributes such as star-freeness [7] on their difficulty as instructions. Our experiments yield multiple hypotheses for what makes instruction learning hard, including evidence that even large transformers struggle with modular counting (e.g., distinguishing even from odd). Here, well-studied attributes of formal languages afford us fine-grained control over the data, precipitating findings that would be difficult and expensive to obtain on natural data. I hope to apply this approach more broadly to isolate and measure progress towards other desirable abilities in LMs.

We can also use formal language theory to derive theoretical results that help us understand neural LMs. I am currently developing a framework for proving **which formal language families**

are learnable by transformers via instructions. This builds on prior work [8], and will hopefully provide bounds on what we can expect transformers to learn from instructions. In the future, I would also like to study **the theoretical implications of sub-task decomposition.** I have previously worked on empirical studies in this area: in my ICLR 2023 submission [9] I implement a modular, recursive LM prompting method which vastly improves generalization to longer sequence lengths compared to other step-by-step reasoning styles. In the future, I am interested in understanding *why* these methods work by formally characterizing the additional computational power that intermediate reasoning affords transformers.

Evaluating general-purpose LMs Comprehensive evaluation is critical to advancing general-purpose NLP systems. For example, existing datasets are too narrow in scope to holistically evaluate math reasoning skills in LMs. To address this, I led 11 researchers in compiling a diverse natural language **math reasoning benchmark**, LĪLA [10] (first-author, EMNLP 2022). We curate over 140K math problems with annotations for reasoning via program synthesis. Our experiments show that multitask learning and augmenting with a Python interpreter massively improve LM performance. Despite our modeling contributions, LĪLA shows that LMs are woefully deficient at math reasoning, and demonstrates the need for unified evaluations of this sort. Going forward, I plan to continue creating thoughtful, comprehensive benchmarks for general-purpose models.

Mitigating risks from general-purpose LMs During my PhD, I also hope to expand research on general-purpose NLP system vulnerabilities and how to mitigate them. For instance, I am developing a decoding procedure where frozen LMs generate their own task-specific prompts. I hope to apply this technique to study **adversarial prompts** that appear to elicit one behavior but cause the model to exhibit another. These prompts could be generated by simultaneously decoding for fluency on one task and accuracy on another. Exposing LM vulnerabilities and finding ways to mitigate them enables progress toward secure and ethical general-purpose NLP systems.

At Stanford I am interested in working with faculty in the Stanford NLP group. There are several professors whose work aligns well with my own, particularly Drs. Percy Liang and Christopher Manning, who share my enthusiasm for understanding LMs as general-purpose NLP systems; and Tatsunori Hashimoto, with whom I would be interested in working on projects that improve LM robustness. I also would be interested in collaborating on linguistically informed approaches to NLP with professors such as Drs. Diyi Yang and Chris Potts. I am confident that Stanford will be an excellent place to pursue a PhD given the large number of faculty working on projects that align with my interests and culture of interdisciplinary research.

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