AI as Thinking Partners: Supporting Experts' Cognitive Workflows

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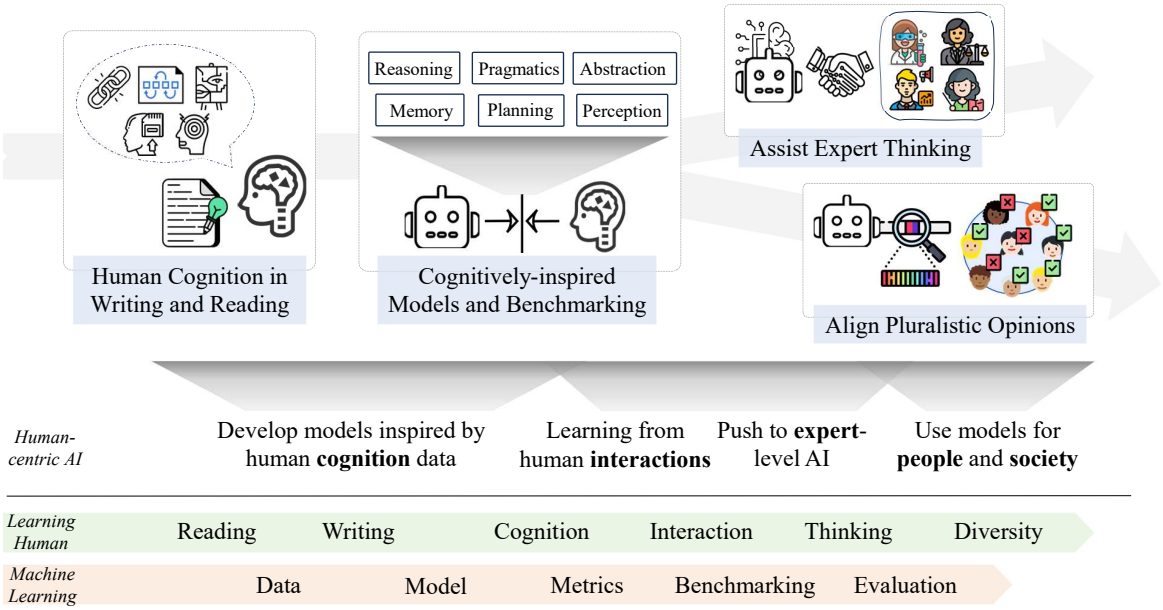
I aim to build human-centric language technologies that cognitively align human and machine thinking, advancing AI as thinking partners for experts. Today's language models still struggle with long-horizon, iterative, self-reflective reasoning, which is essential for high-fidelity decision making in real-world professional work. My work bridges language and cognition to develop novel algorithms, benchmarks, and interaction frameworks that support experts in complex, real-world cognitive workflows. What differentiates my agenda is its training signal: models learn not only from the final text people produce, but from the cognitive processes behind it—keystroke-level revisions, gaze, and expert workflow traces. I design AI that augments humans: models that learn from how people plan, reason, and create; anticipate cognitive bottlenecks; scaffold difficult tasks; and adapt dynamically to expert strategies.



The central premise of my work is that AI should extend and enhance human cognition: supporting expert reasoning, reducing cognitive burdens, and accommodating diverse individual goals. I organize my research into three tightly interconnected pillars: (1) *Cognitive Scaffolding*—collecting human cognition data (§1), building cognitively-aligned AI models (§2), and benchmarking human and machine cognition (§3); (2) *Thinking Assistants for Experts* (§4); and (3) *Societal Alignment* through pluralistic AI (§5).

§1 Collecting Human Cognition Data: Human cognition involves complex, multi-layered thinking processes. For example, writing is a non-linear and iterative cognitive process. By analyzing human writing-process data—such as our *ScholaWrite* corpus of keystroke-level scholarly writing [71] and iterative revision datasets [22, 62, 79]—we can gain insights into these thought processes, which can then be used to improve the planning and reasoning capabilities of AI models [90, 21]. Similarly, human perception can be studied through reading behaviors, such as eye-tracking data or explicit perception annotations, offering clues about how people perceive and process information through reading [30, 14, 34]. Understanding both writing and reading behaviors enables us to enhance the cognitive capabilities of LLMs and develop AI assistants that better support human thinking.

§2 Cognitively-aligned AI Models: Cognitive alignment seeks to extend LLM capabilities to complex human behaviors, including neurosymbolic reasoning [52], task compositionality [90, 29], hierarchical planning [43, 48], abstraction, and social cognition [15]. We develop novel learning paradigms that either mimic human cognitive processes directly or incorporate cognitive data (e.g., writing, reading, expert reasoning, interaction) into training objectives. This includes self-supervised planning, structural and multi-attribute alignment, self-evolving reward models (e.g., Meta Policy Optimization

[60]), and cognitively-efficient modeling strategies.

§3 Cognitive Benchmarking: Current LLM evaluation largely relies on shallow, monotonic tasks. We address this through three directions: (i) assessing both the potential [78, 100, 56, 57, 88, 55, 3] and risks [67, 11, 62, 79] of AI-generated data and AI-based evaluation, identifying issues such as cognitive bias, stylistic artifacts, and shallow synthesis; (ii) building *CogBench*, a large-scale cognitive assessment framework [18, 17] that integrates rigorous cognitive science methodologies with scalable evaluation to contrast human and machine cognition, in open collaboration with interdisciplinary researchers; and (iii) developing long-horizon behavioral evaluation for agentic systems [61, 82].

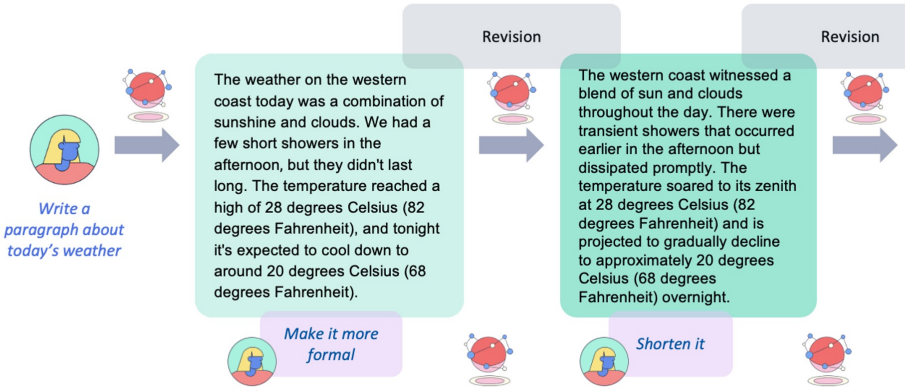
§4 Thinking Assistants for Experts: In domains such as science and law, there is a significant cognitive gap between human experts and current LLMs. We design interactive, domain-specific AI systems that facilitate productive collaboration, adapt to expert workflows, and provide cognitively-aligned assistance. For scientists, we have developed reading tools like *Semantic Reader* [34, 77] and *SciTalk* [87], as well as writing assistants that detect overloaded symbols and discourse-level inconsistencies and promote iterative refinement [21, 71]. For legal professionals, we built *LawFlow* [12], a dataset capturing lawyers' long-horizon planning and reasoning, and are building legal assistants on top of it.

§5 Societal Alignment via Pluralism: AI technologies must reflect diverse human perspectives to achieve societal alignment. We develop data-centric methods to detect, characterize, and augment underrepresented viewpoints [78, 95, 57, 54], and model-centric methods to encode pluralism at individual, group, and societal levels using distributional alignment and societal value modeling [55, 31, 15]. This mitigates risks of monolithic outputs and supports socially inclusive AI.

Together, these agendas form my long-term vision: *human-centric thinking partners* that perform complex, multi-step reasoning, reduce cognitive load, and reflect the diversity and values of human society. My research integrates linguistics, social sciences, and cognitive sciences, and is supported by industry and government partners such as Grammarly, Naver, Google, NSF, Cisco, Sony, Accenture, Thomson Reuters, and Open Philanthropy, with active research collaborations with Amazon, AI2, Naver, and Google. I hold affiliations with cross-college labs at UMN and collaborate widely with faculty and students in computer science, law, psychology, education, journalism, design, and medicine. I also foster cross-community collaboration through workshop organization: I co-organized the first "CtrlGen: Controllable Generative Modeling" workshop at NeurIPS 2021, and founded the "In2Writing: Intelligent and Interactive Writing Assistants" workshop series at ACL 2022, CHI 2023, and CHI 2024, connecting the ML, HCI, NLP, and professional writing communities. I also founded the "Pluralistic Alignment" workshop at NeurIPS 2024 to emphasize diversity in AI.

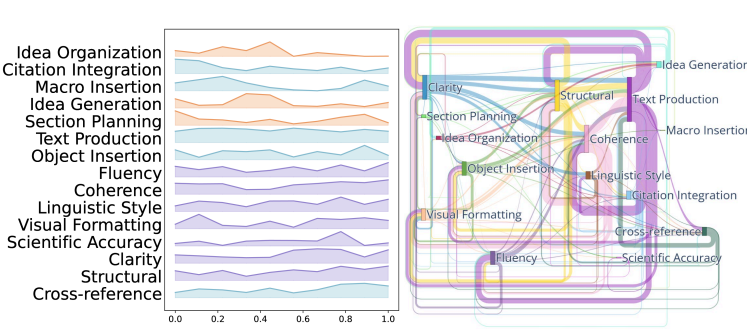
1 Collecting Human Cognition Data

Language serves as a window into human cognition. Writing and reading are not linear acts but complex, iterative processes that reveal how people plan, reason, and perceive information. For example, a well-written manuscript reflects a writer's long-term, multi-stage thinking, far beyond simple next-token prediction. Similarly, reading behaviors captured through eye-tracking or annotated perceptions provide insights into how individuals interpret, learn from, and engage with text. This first research direction—the data foundation of my *Cognitive Scaffolding* pillar—focuses on systematically collecting and analyzing human cognition data from both *production* (writing) and *perception* (reading) to better understand these processes and inform cognitively-aligned AI systems. We call this **cognitive scaffolding**: the systematic use of temporally grounded human cognitive traces—rather than isolated final outputs—as training signals.

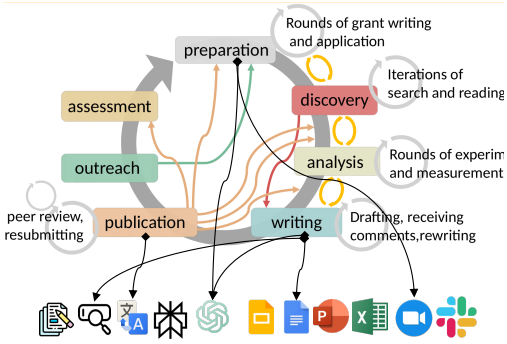


1.1 Writing Data

Human writing involves richer and more deliberate processes than next-token generation: drafting, revising, planning, proofreading, and synthesizing knowledge—often collaboratively. Domain-specific writing, such as drafting scientific manuscripts, adds further challenges, requiring sustained practice, peer interaction, and integration of prior literature. We first examine the *iterative nature of human text revision*. We have collected revision data across domains (*IteraTeR* [22, 59]) and built systems that emulate iterative refinement until quality stabilizes (*R3* [21], *CoEdIT* [90]). Human–AI collaborative editing consistently outperforms either humans or AI working alone [21, 90, 73]. Our studies show that explicitly modeling the revision process—whether through AI alone or human–AI collaboration—consistently yields higher text quality, demonstrating the effectiveness of test-time scaling. Guiding models with human revision intents (e.g., clarity, coherence) further produces revision traces that better mimic the human writing process, making these models better suited to supporting human writers. We also study how varying levels of LLM access reshape writers' behavior [8].



(a) Change of writing intents in scholarly writing [71]



(b) Research Workflow with AI Tools

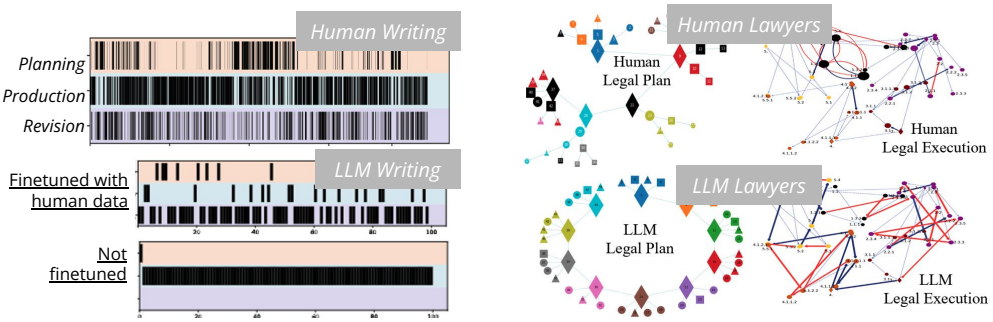
Instead of optimizing isolated skills, we model the coordinated dynamics of full expert processes. In *ScholaWrite* [68, 71], we captured end-to-end scientific writing trajectories—nearly 62K keystroke-level text changes with intention annotations, collected over four months of real manuscript writing—and showed that training on human process data improves alignment and writing quality. This dataset

provides a strong empirical basis for cognitively-aligned writing assistants that model the full lifecycle of text production.

Building on this, the *ScholaWrite2* project is collecting year-long longitudinal research workflows from scientists across domains, including keystrokes, screen and room video from XR glasses, and meeting notes. The collected workflows will be annotated with task intent, cognitive state, and AI-interaction signals, with the goal of formalizing an ontology of real-world scientific reasoning. The resulting corpus forms an **ontology of the scientific process**, enabling training of agents and interfaces that reflect real workflows; relatedly, we find that structured constraints on sensemaking yield more novel research output [80]. Ultimately, we aim to establish a longitudinal repository of cognitive workflows (science, law, education), allowing models to learn not isolated tasks but the temporal dynamics of human reasoning.

1.2 Long-horizon Workflow Data from Domain Experts

My long-term goal is cognitively inspired AI that performs complex, multi-step tasks involving causality, abstraction, and memory while reducing human cognitive load. Such systems require multiple cognitive functions working in concert across an entire workflow (e.g., scientific processes, legal reasoning), not excellence in any single capability. I therefore collect longitudinal workflows from both human experts and LLMs, and use them to improve models' cognitive capabilities on complex, high-fidelity tasks in knowledge-intensive domains.



Left: Scholarly Writing Intents over Time [71], Right: Legal Planning (left) & Execution (right) [12]

Comparing Human and LLM Workflows. The first step is to investigate how human workflows differ from AI workflows and to design methods to align them. Our prior work on collecting long-term human workflow data (in scholarly writing [71] and legal processing [12]) has revealed clear distinctions between human and AI processes. When end-to-end writing data is used to train models to emulate human writing trajectories, the resulting systems exhibit more human-aligned dynamics and improved writing quality [71, 68]. Similarly, in legal planning and execution, we find that humans often act more spontaneously, sometimes repeating inefficient steps [12], whereas AI tends to rigidly follow pre-defined plans. We observe these contrasting behavioral patterns in our study of human- and AI-based legal workflows with practicing lawyers [92], providing key insights for designing cognitively-aligned thinking assistants that better bridge workflows between lawyers and AI agents.

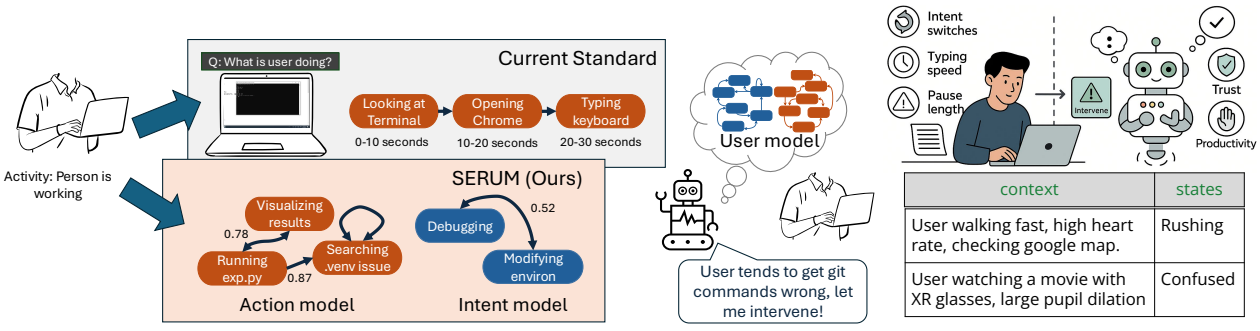
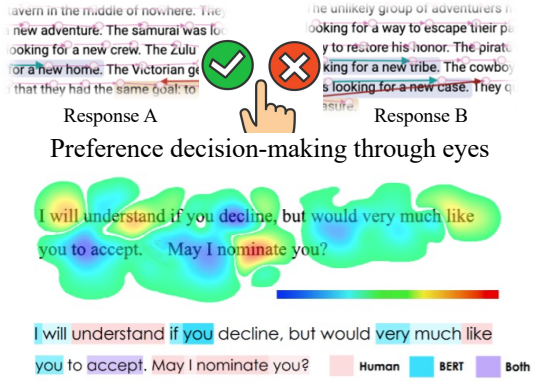


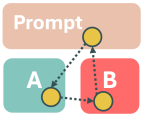
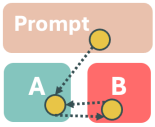
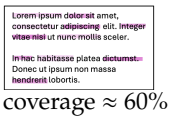
Figure. 2: (Left) SERUM's [89] multi-pass pipeline revisits prior context across frames, enabling the construction of a refined user model for both user actions and intents, enabling better informed proactive suggestions. (Right) Psychometrics from user workflow

User Cognitive Behaviors from Multimodal Context. To scale workflow acquisition beyond keystroke logging and annotation, we are developing multimodal workflow capture and cognitive state modeling. We built systems that extract fine-grained workflow dynamics from raw egocentric YouTube videos (e.g., programming, cooking, tutorials, market research) and infer latent intents using theory-grounded psychometrics. Our platform induces probabilistic finite user state machines (FUSMs)—compact graphs of user actions and the latent intents driving transitions between them—from workflow video via iterative, bottom-up action and intent induction, and derives cognitive metrics from multimodal signals such as gaze, physiology, voice, and video from XR devices. We plan to train lightweight cognitive reasoning models to infer hidden states online and adapt assistance in real time; our *SERUM* framework takes a first step by extracting and refining user states from interaction data [89].

1.3 Reading Data

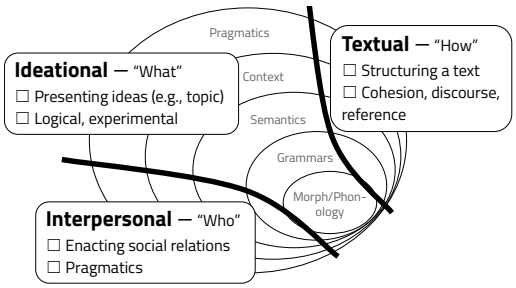


Understanding *politeness* through eyes or annotations

Metric	Illustration	Interpretation
Prompt reread		Indicates uncertainty or careful prompt reconsideration
Response loop		Strong indecision between candidate responses
Read time		Higher values indicate deeper response evaluation
Word coverage	 coverage ≈ 60%	Lower coverage indicates careless reading or a clear-cut decision

Whereas writing data reveals the generative processes of human thought, reading data captures the perceptual and evaluative side of cognition—how people interpret, prioritize, and react to information. We have collected explicit annotations of stylistic understanding [30] and used them to train LLMs that align with readers' stylistic judgments [32]. We have also gathered eye-tracking data to study how readers engage with stylistic cues, narrative content, or preference-ranking annotation tasks [14, 85, 19], showing that gaze patterns provide richer cognitive signals than explicit annotations or model-based interpretations. As shown in the table above, these fine-grained gaze patterns also provide interpretable signals of user behaviors. By collecting data that closely mirrors human perception and evaluative behavior, we aim to train AI systems that more faithfully reproduce human-like decision making and perception processes [55]. These results show that perceptual signals capture evaluative cognition that is systematically absent from text-only supervision; a scaffolding framework for recovering such lost context is developed in [9].

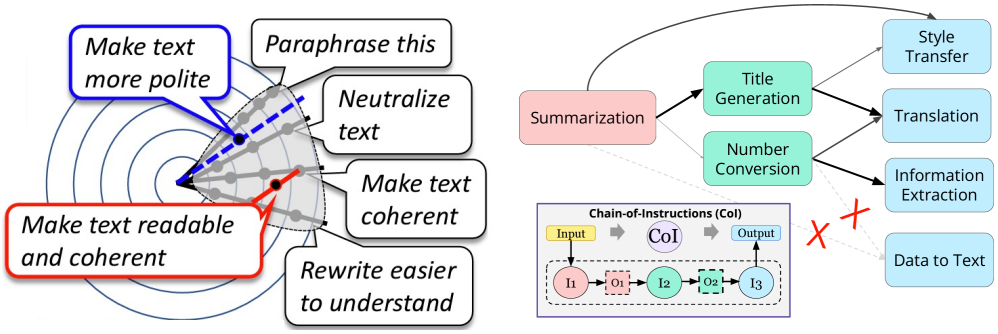
2 Cognitively-aligned AI Models



The goal of *cognitive alignment* is to enhance LLMs' ability to emulate complex human behaviors—such as task compositionality, planning, abstraction, reasoning, and memory—by either (i) mimicking cognitive processes directly or (ii) incorporating human cognition data into training objectives. In line with Halliday's Systemic Functional Linguistics (SFL)—a theory that language simultaneously encodes content, social relations, and structure [41]—these efforts address a single question: how can models internalize human-like structure across reasoning, planning, social judgment, and efficiency?

2.1 Reasoning and Compositionality

Human reasoning often bridges incomplete information through external knowledge and iterative refinement. We integrate neural and symbolic systems [52, 23, 51] to fill knowledge gaps while enhancing interpretability [45]. To test and improve compositionality, we created benchmarks and models for composite and chained tasks—including *CoEdIT*, our publicly released instruction-tuned

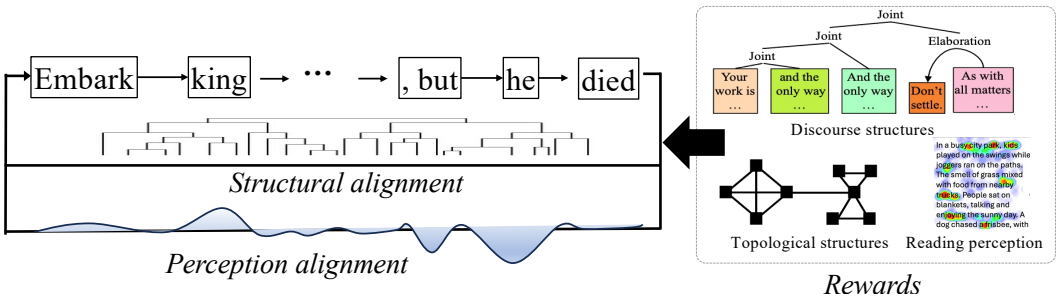


text-editing system [90], and *Chain-of-Instructions* [29]—using compositional data augmentation and task-space densification, i.e., synthesizing training instances for unseen combinations of atomic tasks [6]. Human reasoning is often iterative, refining ideas or solutions step-by-step. We mimic this by developing models that emulate iterative reasoning patterns, showing that step-by-step improvements lead to higher-quality, more diverse outputs [22, 59, 21, 36].

2.2 Planning

Humans achieve coherence by organizing content into a unified structure through decisions about topics, ordering, abstraction, and communication strategy. We therefore model planning as hierarchical optimization of text generation, coordinating multiple text units to guide surface realization.

Discourse-Guided Planning. Coherence emerges from plans that align sentence sequences with discourse goals, grounded in rhetorical structure theory and script theory. We develop supervised planners that incorporate discourse relations [45, 46], topical keywords [48], and social or persuasive goals [28]. Explicit plans based on relations, keywords, and goals enable more controlled, interpretable, and coherent generation through theory-driven discourse guidance [64, 76, 28].

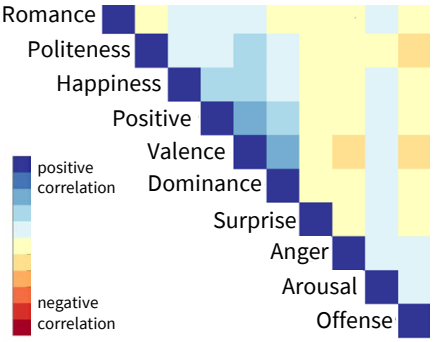


Self-Supervised Planning and Structural Alignment. Large language models rely on next-token prediction, which creates a gap in complex planning and long-horizon writing. We address this gap using alignment methods such as reinforcement learning to optimize high-level policies with human or model-based feedback. Our self-supervised role-playing framework [43] applies reinforcement learning to simulate dialogue interactions and optimize explicit communication goals. This paradigm has evolved into reinforcement learning with AI feedback, where one agent generates text and another provides structured feedback, supporting long-term policy learning. Recent work further aligns text structure with human writing through structural rewards [65, 62, 93, 102] and integrates human perception signals via dense reward alignment, assigning rewards at the span level rather than to whole responses [69].

2.3 Social Cognition

Language encodes interpersonal and societal dimensions of social cognition. Text style emerges from interacting factors such as formality, emotion, and metaphor, reflecting an author's personality and serving specific communicative goals. Understanding these cross-style relationships is key to capturing the nuances of human communication. We built datasets for cross-style analysis, including PASTEL [44] and xSLUE [49], showing that multi-style learning outperforms single-style approaches. Certain style pairs, such as impoliteness–offense, are strongly correlated, while contradictory combinations yield less appropriate outcomes. This underexplored area remains vital

for modeling complex stylistic patterns. More recently, we expanded to high-level affective states such as nostalgia [58] and skepticism [83], collecting annotated data for social cognition research. To align models with multiple social aspects, we developed methods for multi-attribute control via data balancing [13], multi-task fine-tuning [49], policy learning with dynamic reward re-weighting [15], or distillation [7].

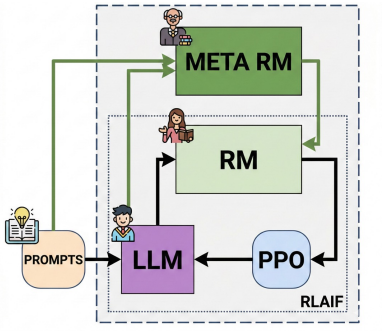


2.4 Cognitive Efficiency

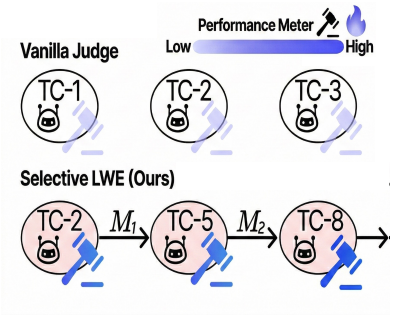
Abstraction enables humans to process knowledge efficiently, bypassing detailed reasoning when shortcuts suffice. Inspired by this, we design algorithms that optimize data usage, computation, and memory in LLM training, reducing hallucinations and improving reliability. Our work includes data-efficient methods that maintain performance with fewer training samples [57, 88], and compute-efficient models that pair parameters across models via dynamic weight warping [81]. We continue to develop cognitively inspired techniques that optimize LLMs' *cognitive utility function*, balancing performance with resource efficiency [96].

2.5 Self-Evolving Agents with Adaptive Cognitive Scaffolding

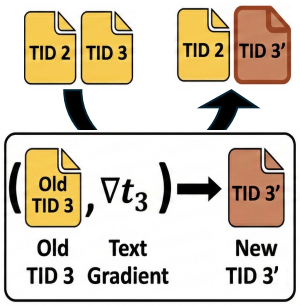
Beyond modeling human workflows, I build agents whose own thinking mechanisms evolve over time. The core idea is to treat long-horizon reasoning as an iterative control problem: agents should revise, critique, and improve their plans and judgments using explicit meta-level feedback or self-reflection on their thinking trajectories, rather than relying on static prompts or fixed reward models.



Meta Policy Optimization



Experienced judging via adaptive prompt update

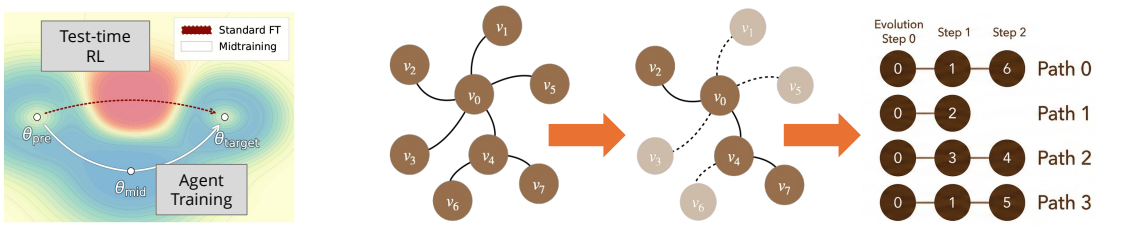


Update thought-templates via text gradients

Our earlier work showed that explicitly modeling revision loops in writing reliably improves quality for both standalone agents and human–AI collaboration, highlighting structured test-time scaling as a principled mechanism for better outcomes [60, 40]. More recently, we focus on methods that update the agent's internal policies and judges as it gains experience. Meta Policy Optimization (MPO) [60] reframes alignment as a two-level adaptive process by dynamically updating the reward model through meta-reward learning, reducing reward hacking by allowing evaluation criteria to change as training reveals new failure modes; *Meta*^{n} generalizes this recursion to multiple meta-levels of self-improvement [63]. Complementary inference-time approaches evolve meta-prompts during deployment, selectively updating them based on self-inconsistency signals to enable continual self-improvement without full retraining [40].

A key technical thread is converting test-time experience into reusable, evolvable knowledge. Instead of compressing long rollouts into a single prompt, we store per-instance reasoning experience as reusable thought-templates, then iteratively refine them using language feedback as text gradients, enabling long-context models to retrieve and apply these templates RAG-style across new tasks [36]. When tool-use experience introduces utility constraints such as budget, latency, and compute, we also model these signals explicitly and learn a meta-utility function at test time via bandit-style optimization, improving test-time decision making under constraints (ongoing work).

Our current emphasis is scalable synthetic collection and selection of complex workflow trajectories [74]. We developed an agent mid-training method, showing that agents fine-tuned with a small set of



high-quality trajectories substantially improve on frontier-discovery and agentic tasks. Across evolving agent frameworks (OpenEvolve, Terminus 2, and OpenHands), we find that trajectory quality and diversity dominate raw scale: selecting about 1K high-quality trajectories from roughly 200K—filtered for branching behavior, refinement strategies, and informative failures—can outperform conventional large-scale Best-of-N and generic test-time training approaches. Curated trajectory data functions as mid-training scaffolding that reduces train–test mismatch.

We explore meta-scaling frameworks (e.g., AsyncThink) that learn how to allocate branching and refinement budgets dynamically across stages of a workflow [24]. In domains with unverifiable judges and multi-step pipelines, such as data analysis and visual insight generation, fixed branching factors waste compute and miss opportunities. Our approach learns stage-specific scaling decisions, for example, increasing parallel exploration when outputs lack diversity or reallocating compute when judge scores are uninformative, yielding more strategic use of fixed compute budgets. Long term, I aim to unify human workflow modeling with self-evolving agent training into efficient agentic learning regimes: systems that learn from expert trajectories, accumulate test-time experience as structured memory, and continuously improve their reasoning policies and evaluation criteria.

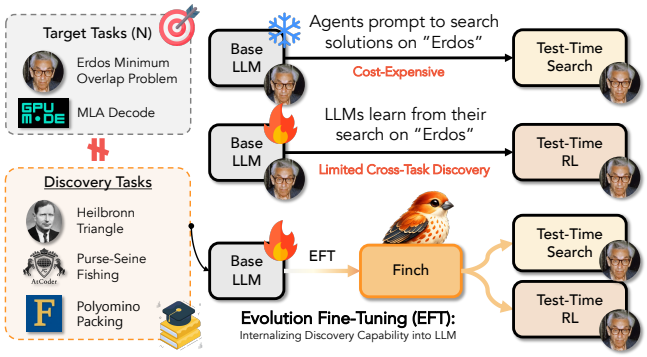


Figure. 3: Evolution Fine-Tuning (EFT) [74]

2.6 Extension to Other Modalities

While my work primarily focuses on language, multidisciplinary collaborations have extended it to images and video, showing that multimodal models benefit from complementary cross-modal effects. Effective multimodal learning, however, requires careful design of fusion strategies and cognitive objectives such as reasoning and planning. Key results include the following: (i) vision–language models improve understanding of global connectivity and graph motif analysis in graph images [10], (ii) explicit temporal memory in video LLMs yields more coherent frames [4], (iii) aligning vision–language models with LLM feedback enhances reasoning in video and image tasks [53, 3, 2, 84], (iv) integrating multimodal representations into a unified latent space (a "Platonic" representation, where different modalities converge to a shared underlying structure) accelerates cross-modal understanding [35], and (v) LLMs can plan robotic manipulation tasks from language-based instructions [97]. Beyond multimodality, I also explore (i) autoregressive–diffusion hybrids for text generation [103], (ii) model uncertainty and calibrated abstention [38, 57, 66, 101] and generalization [1, 39], and (iii) theoretical analyses of learning frameworks [75].

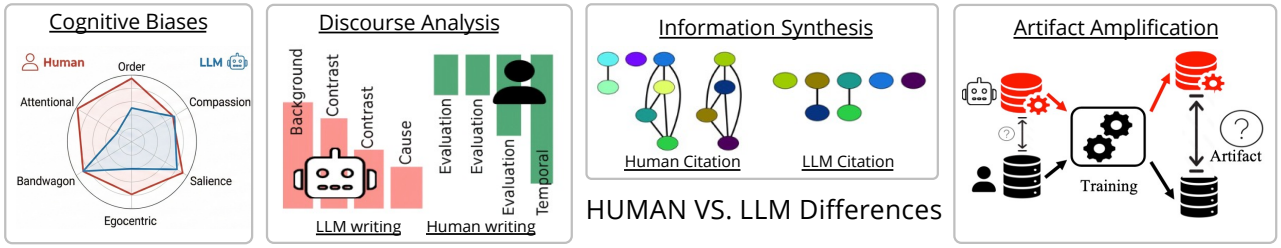
3 Cognitive Benchmarking and Evaluation

Evaluation is undergoing a structural shift as LLMs move from standalone models to persistent, tool-using collaborators embedded in real workflows. In this setting, leaderboard-style testing on fixed benchmarks is insufficient: evaluation becomes a measurement engineering problem, where the goal is to produce metrics that remain valid, interpretable, and safety-relevant as models, data, and deployment contexts drift; our recent benchmarks make evaluation principles and test difficulty explicit [33, 5]. My work develops evaluation methods and infrastructure across three directions: (i) quantifying the benefits and risks of AI-generated data and LLM-based evaluation, (ii) benchmarking human and machine cognition with theory-grounded assessments, and (iii) replacing static benchmarking

practices with long-horizon behavioral measurement for agentic systems [61, 82].

3.1 Potentials and Risks of AI-generated Data

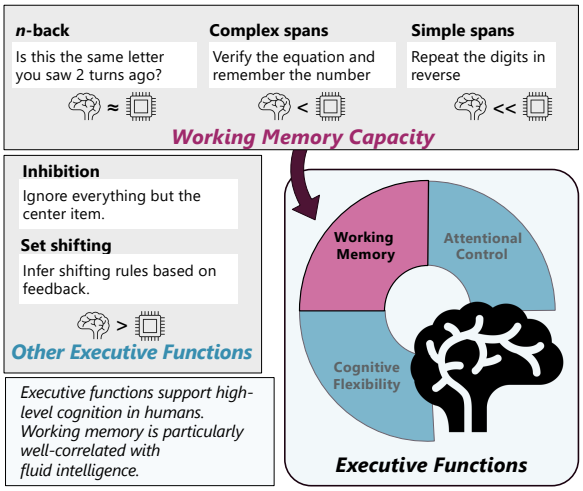
As LLMs began replacing or supplementing human annotation, I studied both the acceleration they enable and the new failure modes they introduce, including opaque error provenance and artifact reinforcement. On the opportunity side, I developed cost-reducing supervision and data-expansion techniques via symbolic rules [23, 52], annotation imputation [78], and information-theoretic measures [56, 57, 88, 66], as well as disagreement-aware sampling [95]. LLMs can generate annotations, prompts, simulated dialogues, and evaluation data, accelerating the research and development process. We have leveraged LLM-based evaluations [55, 3] and multi-agent simulations [43, 6, 98] to enrich training data.



In parallel, I characterized how overreliance can create an artificial data ecosystem (*Artifactuality* [11]) that distorts measurement and behavior through cognitive biases (*CoBBLEr* [67, 50]), discourse shifts [62], shallow synthesis [79], artifact amplification [11], and behavioral inconsistency across tasks and contexts [82, 94]. These results motivate evaluation protocols that explicitly model feedback loops between generators, judges, and downstream learners, rather than treating synthetic data and LLM judges as neutral measurement instruments.

3.2 Cognitive Assessment of LLMs

Traditional cognitive science experiments provide detailed insights into human cognition but are difficult to scale, creating a bottleneck for theory-driven data. To address this, we are developing *CogBench*[1], a benchmarking framework that connects cognitive psychology with artificial intelligence. CogBench integrates controlled human experiments with systematic evaluation of LLMs across executive control, working memory, temporal reasoning, and narrative comprehension. Although LLMs often perform well superficially, our findings reveal key cognitive limitations compared to humans. Models show a gap between capacity and control, with high working memory capacity but weak executive control and cognitive flexibility, as seen in tasks such as the Wisconsin Card Sorting Test [17]. They also rely heavily on prototypical patterns, producing inconsistent temporal and causal judgments in narratives [18, 91]. Moreover, while internal representations can detect incoherence, model outputs do not reliably distinguish coherent from incoherent narratives [16].



Limited executive functioning in LLMs [17]

By grounding AI evaluation in cognitive science and scaling it through benchmarking, CogBench characterizes the cognitive limits of current AI systems and provides the foundation for expert-facing systems where cognitive alignment can be assessed end to end.

Toward Long-horizon Agentic Evaluation. Finally, as LLMs become agents embedded in extended workflows, we move beyond static benchmarks toward behavioral measurement over long, multi-step episodes. Our recent studies show that current LLM agents are strong tool users but weak navigators

[1] https://minnesotanlp.github.io/CogBench-web/

of long-horizon tasks [61], and that their behavior is often inconsistent across tasks and contexts [82], motivating persistent, workflow-embedded evaluation of agentic systems.

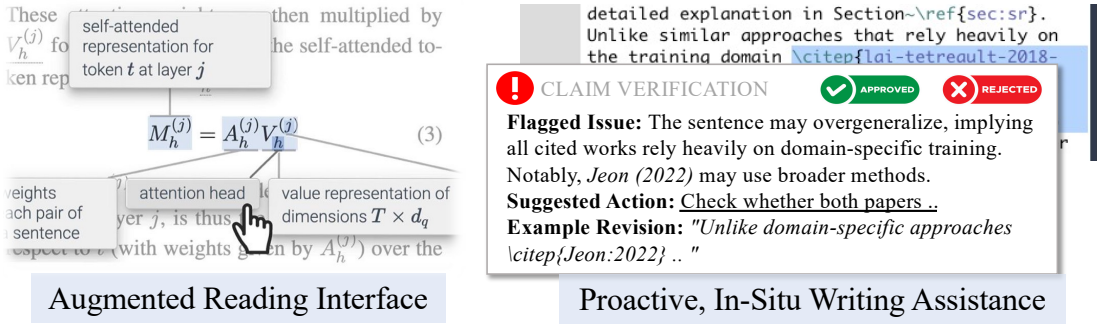
4 Thinking Assistants for Experts

In knowledge-intensive domains such as scientific research and legal practice, significant cognitive gaps remain between human experts and current LLM capabilities. These gaps arise from limitations in handling complex multi-step tasks, incorporating dynamic feedback, and adapting to evolving contexts. Full automation often oversimplifies the nuanced reasoning these tasks require, leaving AI systems misaligned with expert workflows.

My objectives are twofold: (i) benchmark AI cognition on end-to-end professional tasks to identify cognitive gaps, and (ii) create collaborative platforms where experts and AI agents interact, exchange feedback, and adapt over time. We focus first on building expert support systems in two flagship domains—*science* and *law*—and extend to media domains such as advertising and journalism (§4.3).

4.1 Assistants for Scientists

Reading Assistance. In collaboration with AI2 and UC Berkeley, I contributed to the development of *Semantic Reader* [34, 77], a tool publicly deployed on Semantic Scholar that provides in-situ definitions and explanations of terms as scientists read papers [47, 37], thereby reducing cognitive load. More recently, we launched *SciTalk*, which transforms research papers into short-form videos, making knowledge more accessible to wider audiences [87].



Augmented Reading Interface | Proactive, In-Situ Writing Assistance

Writing Assistance. Scientific writing is a paradigmatic case of the iterative cognitive processes described in §1. I envision the future of scientific writing as a collaborative effort between scientists and AI agents, where both iteratively co-develop high-quality research outputs.

Writing assistance must go beyond supporting the immediate writing context. It should understand the full workflow, capturing the writer's intent and providing in-situ support while minimizing distraction. I also focus on building interaction-centric AI systems that evolve through user feedback to better support scientific writing.

Our design principles include:

- *In-Situ Aids for Writing*: Document-level tools that detect overloaded symbols, redundant terminology, and logical inconsistencies using discourse-level modeling for real-time writing support.
- *Workflow-aware Interfaces*: Features that flag inconsistent scientific claims or overstated text and suggest revisions. For instance, a scientist drafting a related work section in Overleaf may trigger backend reasoning agents to automatically retrieve cited literature, detect errors or overstatements, and suggest improved citations with inferred rationales.
- *Human-Centric Design and Co-Learning*: Avoiding the "illusion of clarity" [86] by carefully designing interfaces that support scientists' thinking processes while reinforcing human–AI collaboration.
- *Learning from Human Workflow*: Collecting human revision and writing workflow data to build cognitively-aligned systems for naturally integrated interactions [21, 71, 73, 98].
- *Learning from Interaction*: Adaptive systems that improve via user feedback, as demonstrated in collaborative editing [21] and iterative taxonomy building [72].

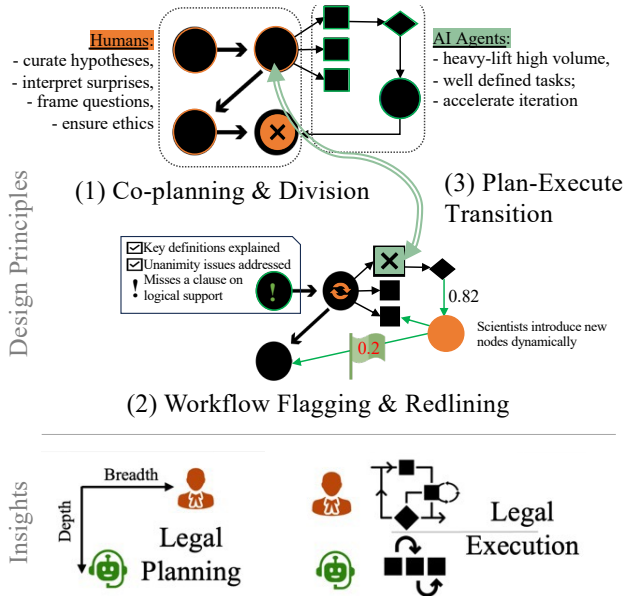
- *Trustworthy Models*: With NSF support, we develop foundation models integrating reliable, cross-modal knowledge for robust writing assistance.

Other Scientific Tasks. Beyond reading and writing, scientific workflows involve cognitively demanding stages such as peer review, collaboration, experimentation, and verification. Our lab is developing specialized agents and interfaces to support different stages of scientific tasks. For instance, we created *PeerRead* [42] (NAACL 2018), the first large-scale dataset of papers and reviews from computer science conferences, enabling research on acceptance prediction and aspect-specific review generation. In collaboration with visualization researchers, we are also building systems that automatically generate effective visualizations and insights (*A2P-Vis* [25]) and that scaffold the design of multi-agent analysis workflows (*FlowForge* [27]), adapting interactively to scientists' needs.

4.2 Assistants for Lawyers

With Open Philanthropy and UMN Law School, we developed *LawFlow* [12], a benchmark for complex legal processing tasks requiring long-horizon reasoning and planning. The dataset captures detailed workflow data from both human lawyers and AI agents, including brainstorming, planning, research, and client communication for tasks such as advising a startup.

Our findings reveal that human legal reasoning is recursive and exploratory, whereas AI workflows are typically linear and exhaustive. From these human–AI comparisons, we derive design principles for legal interfaces, including collaborative planning, task division, and workflow flagging, and we are actively developing interfaces guided by these insights. Reflections from practicing lawyers [92] further highlight that generative AI already improves junior lawyer performance, yet adoption lags because evaluating AI outputs is cognitively demanding, especially for less experienced practitioners.



These challenges create several risks, including overtrust or overreliance on AI, shortcut-driven reasoning [70], and the potential intensification of expert polarization. Junior lawyers in particular risk being sidelined without proper scaffolding. To mitigate these risks, we emphasize the need for tools that upskill junior lawyers, train them to critically validate AI outputs, and provide workflow-aware assistance that supports lawyers as thinking and co-learning partners, ultimately lowering cognitive burden rather than replacing expertise.

4.3 Advertising and Journalism

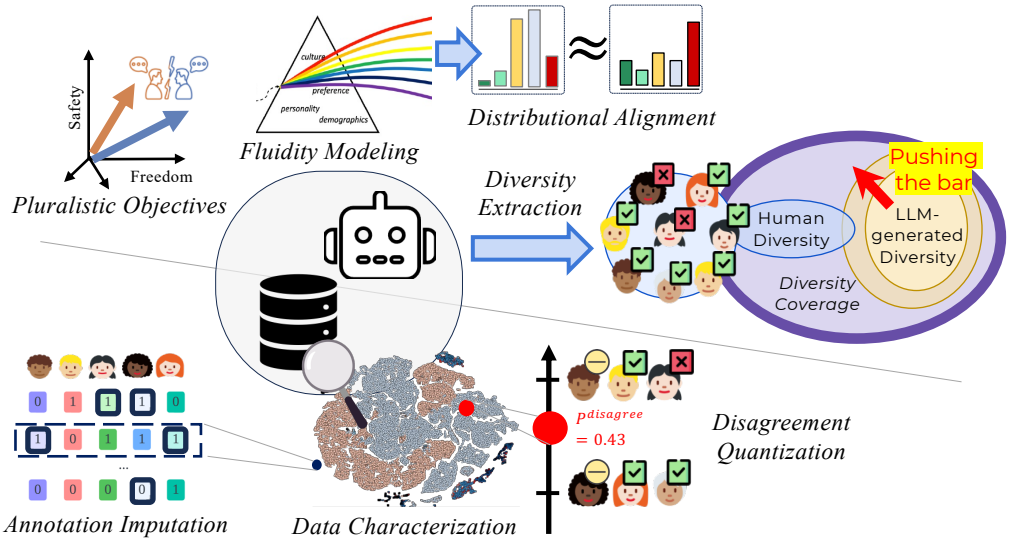
Advertising and journalism are expert domains where nuanced affective responses, not just factual accuracy, drive outcomes. In collaboration with Naver and MCAL, I contribute to developing computational metrics and algorithms for advertising in both academia and industry. For example, in the advertising market, we model nuanced affective responses such as skepticism [83] and nostalgia [58], moving beyond sentiment-based metrics. Recently, we have also studied how advertising is shifting from keyword-based search advertising toward generative ad platforms (e.g., Perplexity, Google AI Overviews), conducting comparative research on search patterns and consumer engagement to better understand the impact of AI on the advertising ecosystem [26]. Finally, I have worked on transforming the workflows of advertising services by integrating AI technologies. For instance, we are developing ad systems that support off-policy evaluation (OPE)—estimating the value of new ad policies from logged data without live deployment—in deterministic environments such as ad auctions [99].

By capturing detailed expert reasoning, we aim to build cognitively inspired models and expert-aware interfaces that adapt to the dynamic cognitive states of professionals. This approach will extend to other domains such as education [20], medicine, and programming, forming a broad *Expert Benchmarking* initiative to support specialized AI systems tailored to the cognitive demands of diverse expert roles.

5 Societal Alignment via Pluralism

Our society thrives on diverse perspectives shaped by different backgrounds, identities, and cultures, yet rapid AI advances often collapse them into a generalized "average." Because cognition itself is pluralistic, alignment is not an add-on but a core requirement of cognitively-aligned AI: we must build people-centric technologies that capture and encourage diversity, ensuring inclusivity and societal alignment.

My goal is to build socially aware AI models that represent the full spectrum of human opinions through two complementary approaches: **data-centric** (§5.1) and **model-centric** (§5.2).



5.1 Data-centric Alignment

Diversity is difficult to define and capture: it manifests at individual, group, and community levels, and varies over time and context. Our "pluralistic representation" approach encodes disagreement and perspective variation directly into datasets. We develop methods to detect, characterize, and augment marginal viewpoints by (i) predicting missing annotations with collaborative filtering over annotations [78], (ii) analyzing annotation properties via learning dynamics [57], (iii) quantifying the disagreement level using demographic factors [95], and (iv) collecting perspectives from language learners to diversify model predictions [100, 54].

5.2 Model-centric Alignment

As NLP tasks grow more subjective, labels often shift from discrete to continuous values. Models that ignore this fluidity risk excluding certain groups. We design pluralistic alignment methods at multiple granularity levels: (i) *Individual preferences:* Model disagreement as a proxy for diversity using pairwise preference learning [55], (ii) *Group distributions:* Extract diverse opinions from LLMs [31] and align them with survey-based population distributions, and (iii) *Societal values:* Dynamically combine and resolve value conflicts using crowdsourced resolution scenarios [15].

As AI becomes embedded in education, industry, and politics, systems that ignore plurality risk amplifying monolithic perspectives and deepening polarization; pluralistic AI instead models coexistence among differing values, beliefs, and cultural backgrounds. To build a research community around these questions, I founded the Pluralistic Alignment workshop at NeurIPS 2024, bringing together ML, HCI, and social science researchers. My future work will operationalize pluralistic alignment through quantitative diversity metrics, disagreement-aware training objectives, and cross-cultural evaluation datasets.

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