

# Atharva Naik

✉ [arnaik@andrew.cmu.edu](mailto:arnaik@andrew.cmu.edu)

🐙 [atharva-naik](https://github.com/atharva-naik)

🌐 [Atharva Naik](#)

🌐 <https://atharva-naik.github.io/>

🔍 [Google Scholar](#)







## Education

- 2024 – . . . .  **Ph.D. Language Technologies, Carnegie Mellon University.**  
Advisors: [Carolyn Rose](#), [Daniel Fried](#)  
GPA: 4.14/4
- 2022 – 2024  **M.S. Language Technologies, Carnegie Mellon University**  
GPA: 4.11/4
- 2018 – 2022  **B.Tech. Computer Science, Indian Institute of Technology, Kharagpur**  
GPA: 9.66/10

## Research



**Statement:** My research focuses on developing synthetic data generation and post-training methods to build Large Language Models of Code that can adapt to contextual knowledge, handle shifting data distributions, and reason dynamically at test time. I aim to apply these capabilities to (1) code quality and review, (2) reasoning, and (3) code security and AI safety.

## Experience

- 2025  **Research Intern, Oracle Labs** MetaLint: Generalizable Idiomatic Code Quality Analysis with Instruction Following and Easy-to-Hard Generalization
- 2022 – 2024  **Research Assistant, Carnegie Mellon University** Reinforcement Learning for Code Quality & Review, Reasoning for AI Safety, Programming by Examples for Reasoning
- 2021  **Research Intern, Technische Universität Darmstadt** Neural Network Architecture for Faithful Interpretability in NLP.
-  **Research Intern, Adobe** RL agent for Creative Human-Human Collaboration.
-  **Research Intern, University of Alberta** Neuro-Symbolic Fuzzy Logic-based Reasoning for Explainable Natural Language Inference.
- 2019-2020  **Student Researcher, Autonomous Ground Vehicle (AGV) Group** Path Planning and Localization for Autonomous Driving.

## Publications

### Conference Publications

- 1 **A. Naik**, D. Agrawal, H. Sng, *et al.*, “Programming by example meets historical linguistics: A large language model based approach to sound law induction,” in *ACL*, 2025, pp. 29 628–29 647.  URL: <https://aclanthology.org/2025.acl-long.1432/>.
- 2 **A. Naik**, M. Alenius, D. Fried, and C. Rose, “CRScore: Grounding automated evaluation of code review comments in code claims and smells,” in *NAACL*, 2025, pp. 9049–9076.  URL: <https://aclanthology.org/2025.naacl-long.457/>.
- 3 S. Gandhi, **A. Naik**, Y. Xie, and C. Rose, “An empirical study on strong-weak model collaboration for repo-level code generation,” in *EMNLP (to appear)*, 2025.
- 4 **A. Naik**, J. R. Yin, A. Kamath, *et al.*, “Generating situated reflection triggers about alternative solution paths: A case study of generative ai for computer-supported collaborative learning,” in *AIED*, 2024.

- 5 **A. Naik**, J. R. Yin, A. Kamath, *et al.*, “Providing tailored reflection instructions in collaborative learning using large language models,” in *BJET*, vol. 56, 2024, pp. 531–550.
- 6 A. Rao, S. Vashistha, **A. Naik**, S. Aditya, and M. Choudhury, “Tricking LLMs into Disobedience: Understanding, Analyzing, and Preventing Jailbreaks,” in *LREC-COLING*, 2024.
- 7 **A. Naik**, S. Das, J. Vedurada, and S. Aditya, “Sync: A structurally guided hard negative curriculum for generalizable neural code search,” in *AACL*, 2023.
- 8 Z. Wu, Z. X. Zhang, **A. Naik**, Z. Mei, M. Firdaus, and L. Mou, “Weakly Supervised Explainable Phrasal Reasoning with Neural Fuzzy Logic,” in *ICLR*, 2023.
- 9 Y. Xie, **A. Naik**, D. Fried, and C. Rose, “CMTrans: Improving Code Translation with Comparable Corpora and Multiple References,” in *EMNLP Findings*, 2023.
- 10 S. Bv, J. A. Patel, **A. Naik**, Y. Butala, S. Sharma, and N. Chhaya, “Towards Enabling Synchronous Digital Creative Collaboration: Codifying Conflicts in Co-Coloring,” in *CHI Extended Abstracts*, 2022.
- 11 B. Santra, S. Roychowdhury, A. Mandal, *et al.*, “Representation Learning for Conversational Data using Discourse Mutual Information Maximization,” in *NAACL*, 2022.
- 12 Y. Wang, S. Mishra, P. Alipoormolabashi, *et al.*, “Super-NaturalInstructions: Generalization via Declarative Instructions on 1600+ NLP Tasks,” in *EMNLP*, 2022.
- 13 R. Mukherjee, **A. Naik**, S. Poddar, S. Dasgupta, and N. Ganguly, “Understanding the Role of Affect Dimensions in Detecting Emotions from Tweets: A Multi-task Approach,” in *SIGIR*, 2021.

## Preprints

- 1 **A. Naik**, A. Xie, A. Rao, *et al.*, “Secure and useful models are reasonable: Aligning code models via utility-preserving reasoning,”
- 2 **A. Naik**, D. Agrawal, M. Kapadnis, *et al.*, “Pbebench: A multi-step programming by examples reasoning benchmark inspired by historical linguistics,” *arXiv preprint arXiv:2505.23126*, 2025.
- 3 **A. Naik**, L. Baghel, D. Govindarajan, D. Agrawal, D. Fried, and C. Rose, “Metalint: Generalizable idiomatic code quality analysis through instruction-following and easy-to-hard generalization,” *arXiv preprint arXiv:2507.11687*, 2025.
- 4 M. N. Kapadnis, **A. Naik**, and C. Rose, “Crsscore++: Reinforcement learning with verifiable tool and ai feedback for code review,” *arXiv preprint arXiv:2506.00296*, 2025.
- 5 **A. Naik**, “On the limitations of embedding based methods for measuring functional correctness for code generation,” *arXiv preprint arXiv:2405.01580*, 2024.
- 6 **A. Naik**, K. Zhang, N. Robinson, *et al.*, “Can large language models code like a linguist?: A case study in low resource sound law induction,” 2024. arXiv: 2406.12725 [cs.CL].

## Projects

### MetaLint:

- Developed MetaLint, an instruction-following framework that detects and corrects non-idiomatic Python and Java code by aligning with evolving PEP and JEP standards. Utilized instruction fine-tuning and Direct Preference Optimization (DPO) to enable test-time adaptation to novel idioms.
- Achieved state-of-the-art recall of 70.43% for idiom detection and 26.73% for line-level localization on a challenging PEP-based benchmark, performing similarly to models like o3-mini despite using only a fine-tuned 4B parameter model.

## Projects (continued)

- Demonstrated robust generalization across programming languages, model families, linters, and reasoning settings, highlighting MetaLint's adaptability to diverse code quality analysis tasks.

### PBEBench:

- Developed PBEBench, a scalable, contamination-free benchmark generator for evaluating LLMs' inductive reasoning and planning in a knowledge free setting via multi-step string rewrite tasks, controlling difficulty with required rewrite steps, ordering constraints, and number of string examples.
- Analyzed reasoning bottlenecks and test-time scaling strategies, measuring performance saturation across top open and closed-source models like gpt-oss-120B and GPT-5.
- Found that while state-of-the-art reasoning models outperform non-reasoning LLMs, none yet achieve expert human-level performance on realistic historical linguistics tasks.

### Programming by Examples Meets Historical Linguistics:

- Framed sound law induction (SLI) in historical linguistics as a programming-by-examples task and leveraged code LLMs to generate and evaluate Python sound law program, using synthetic data to improve their accuracy in explaining sound change examples.
- Showed that logically structured synthetic programs with realistic inputs outperform training on real sound law programs, highlighting key factors about the training data distribution for successful SLI.
- Accepted as an ACL long track oral presentation (top 10% of papers).

### CRScore:

- Developed a reference-free metric for code review comment generation by combining LLMs and static analysis to produce pseudo-reference rubrics and interpretable scoring coverage across key quality dimensions using semantic embedding based similarity.
- Achieved second-highest correlation with human judgment after GPT-4o using a 7B Magicoder model, outperforming it as a direct judge and reducing evaluation complexity from  $O(m \times d)$  to  $O(d)$  ( $m$  - number of models evaluated,  $d$  - number of datapoints).
- Accepted as a NAACL long track oral presentation.

## Skills

Coding	■ Python (expert), C/C++, Bash (familiar), Javascript (novice)
Frameworks	■ vLLM, DeepSpeed, PyTorch, HuggingFace, Fairseq, NLTK, spaCy, Tensorflow, FastAPI, Flask, Django, PyQt5, Jupyterlab, OpenCV, Git

## Achievements

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|------|---|
| 2025 | ■ <b>Amazon Trusted AI Challenge Finalist</b> , Led the Carnegie Mellon University team to the finals as one of the top four defender teams for developing secure code LLMs.                  |
|      | ■ <b>ACL 2025 Oral Presentation</b> , One of 243 papers selected from over 3,000 accepted submissions.  |
| 2024 | ■ <b>Amazon Trusted AI Challenge Top 10 Team</b> , Selected among 90 applicant teams and awarded a \$250K research grant as team lead for CMU to advance the development of secure code LLMs. |
|      | ■ <b>Best Paper &amp; Best Student Paper Nominations</b> , Artificial Intelligence in Education (AIED 2024).  |
| 2022 | ■ <b>2nd Place</b> , Deep Learning Labs OpenAI GPT-3 Hackathon.   |

## Achievements (continued)

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- 2021
  - **DAAD WISE Scholarship.**
  - **MITACS Globalink Scholarship.**
  - **Bronze**, Inter IIT Technology Meet (IIT Kharagpur contingent).
- 2019
  - **2nd Place**, Intelligent Ground Vehicle Competition (IGVC).
- 2018
  - All India Rank **1248** in JEE Advanced and **1618** in JEE Mains among 1M candidates.
  - **Kishore Vaigyanik Protsahan Yojana (KVPY) Scholarship.**