SAMYAK JAIN

(+91)9179144039 \diamond samyakjain.cse18@itbhu.ac.in \diamond DOB: 1 st December, 1999 LinkedIn \diamond Github \diamond Webpage \diamond Google Scholar \diamond Twitter

EDUCATION

Indian Institute of Technology (BHU) Varanasi

August 2018 - May 2023

Integrated Dual Degree (B.Tech + M.Tech) in Computer Science - CGPA: 9.55/10.0 Master's Thesis

AREAS OF INTEREST

AI Alignment, Science of Deep Learning, Interpretability, Understanding Learning Dynamics

EXPERIENCE

Microsoft Research India Research Fellow	July 2024 - Present Mentor Navin Goyal
Five AI and Torr Vision Group, Oxford Research Intern	October 2023 - June-2024 Mentor Puneet Dokania
Krueger AI Safety Lab, Cambridge University Research Intern	May 2023 - October-2023 Mentor David Krueger
Vision and AI Lab, Indian Institute of Science, Bangalore Research Intern	May 2020 - May-2023 Mentor Venkatesh Babu
Theoretical Foundations of AI, Technical University of Munich Research Intern	May 2021 - August-2021 Mentor Debarghya Ghoshdastidar

PUBLICATIONS

- What Makes Safety Fine-tuning Methods Safe? A Mechanistic Study
 Samyak Jain, Ekdeep Singh, Kemal Oksuz, Tom Joy, Phil Torr, Amartya Sanyal, Puneet Dokania ICML workshop on Mechanistic Interpretability, 2024 (Spotlight)
 NeurIPS 2024 [main]
- 2. Mechanistically analyzing the effects of fine-tuning on procedurally defined tasks

 Samyak Jain*, Robert Kirk*, Ekdeep Singh*, Hidenori Tanaka, Robert Dick, Tim Rocktaschel, Edward

 Grefenstette, David Krueger

 ICLR 2024 [main][code]
- 3. DART: Diversify-Aggregate-Repeat Training Improves Generalization of Neural Networks Samyak Jain*, Sravanti Addepalli*, Pawan Sahu, Priyam Dey, RV. Babu CVPR-2023 [main][code]
- 4. Efficient and Effective Augmentation Strategy for Adversarial Training Sravanti Addepalli*, Samyak Jain*, RV. Babu NeurIPS 2022 [main][code]
- 5. Scaling Adversarial Training to Large Perturbation Bounds Sravanti Addepalli*, Samyak Jain*, Gaurang Sriramanan, RV. Babu ECCV 2022 [main][code]
- 6. Boosting Adversarial Robustness using Feature Level Stochastic Smoothing Sravanti Addepalli*, Samyak Jain*, Gaurang Sriramanan*, RV. Babu SAIAD Workshop CVPR 2021 [main][code]
- 7. Towards Understanding and Improving Adversarial Robustness of Vision Transformers

 Samyak Jain, Tanima Dutta

 CVPR 2024 [main]

ACADEMIC PROJECTS AND COLLABORATIONS

Understanding the role of inductive biases of loss landscape in convergence Navin Goyal

• Analyzing the connections between Bayesian posterior of high likelihood models and lottery ticket hypothesis using mechanistic interpretability and their role in convergence of the model.

Mechanistic understanding of safety fine-tuning and jailbreaking attacks Puneet Dokania, Ekdeep Singh, Amartya Sanyal, Phil Torr

- Safety fine-tuning projects unsafe samples into model's (low rank) null space, resulting in safety.
- Model is unsuccessful in projecting jailbreaks into its null space, thus circumventing the safety.
- Gemma Scope highlighted value of using sparse autoencoders in LLMs based on insights in this work.

Mechanistic understanding of fine-tuning Robert Kirk, Ekdeep Singh, David Krueger

- Demonstrated that fine-tuning is unable to alter the model mechanistically, giving pretense of change.
- Reverse fine-tuning has become the staple method for evaluating unlearning.
- This work is often used to counter use of safety-finetuning as an assurance protocol. Some works [1], [2] have used this work to submit comments to **RFI related to NIST's** executive order concerning AI.

Exploring loss basin to find generalized solutions RV. Babu, Sravanti Addepalli

- Showed that using weight averaging of diverse models during training increases the convergence time for learning spurious features and aids the learning of robust features.
- Proposed method DART shows improvements on both in-domain and out of domain settings.

Using data augmentations effectively in adversarial training RV. Babu, Sravanti Addepalli

- Demonstrated for the first time that it is possible to use augmentations effectively in adversarial training irrespective of the type of augmentation and adversarial training (AT) method used.
- Demonstrated that weight space smoothing can help in preventing catastrophic overfitting.

Aligning adversarial training with Ideal training objectives RV. Babu, Sravanti Addepalli

- Observed that standard AT cannot generalize to larger perturbation bounds due to conflict in training.
- Developed Oracle-Aligned Adversarial Training (OAAT), which aims to align the model's predictions with the oracle labels of adversarial images.

Calibrating robust models to allow rejection of adversarial samples RV. Babu, Sravanti Addepalli

- Inspired by variational inference, proposed a stochastic classifier which aims to learn smoother class boundaries by sampling noise multiple times in its latent space during inference.
- Proposed method demonstrated improved robustness along with improved calibration.

Understanding gradient masking in vision transformers Tanima Dutta

- Past works have demonstrated gradient masking in vision transformers, but failed to analyze the cause.
- Demonstrated that softmax in attention causes floating point errors leading to gradient masking in VITs.

SCHOLASTIC ACHIEVEMENTS

- Recipient of **DAAD-WISE**, a research oriented scholarship program by German Government.
- Fellow of Berkeley Existential Risk Initiative (BERI), which supported my research at Cambridge.
- Recipient of Summer Research Fellowship 2020 (SRFP), a research program by Indian Government.
- All India rank 922 in JEE Advanced 2018 and 346 in JEE Mains 2018 out of 1 million+ candidates.
- Selected for the KVPY 2018 Fellowship (IISc, Bangalore) by the Govt. of India.
- Ranked in amongst Top 300 students in India for Maths, Physics and Astronomy Olympiads at national level – INMO, INPhO, INAO 2018 and city topper in NTSE 2016.

FEATURED POSITIONS

Reviewer: NeurIPS 2024, ICLR 2024, ICML 2023, NeurIPS 2023, CVPR 2023 (outstanding reviewer), CVPR 2022 (outstanding reviewer), ICLR 2022 (highlighted reviewer), ECCV 2022, NeurIPS 2022. Teaching Assistant: Introduction to Database Management, Introduction to Machine Learning

• Conducted lab classes of undergraduate students with a batch size of over 80 students and managed lab evaluations along with assignments.