

Adrian Chang

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EDUCATION

Brown University, *Sc.B. Computer Science Honors*, 3.95/4.0 GPA

Providence, RI | Class of 2023

Pacific Ridge Highschool, 4.50/4.00 GPA

Carlsbad, CA | Class of 2019

TECHNICAL EXPERIENCE

Vision Systems Inc, *Research Developer*

Cambridge, MA | May 2023 - Present

- Researcher on the IARPA WRIVA program
- Experience with **NeRF** and **3D Gaussian Splatting** for sparse view 3D reconstruction and mixed modality imagery (aerial + ground)

Brown University, *Undergraduate Research Assistant*

Providence, RI | January 2022 - May 2023

- Undergraduate Research Assistant in the Brown Visual Computing Lab advised by Daniel Ritchie researching **Neurosymbolic Indoor Scene Synthesis**
- Experience training and designing **Transformers** in **PyTorch**
- Experience with **Neuro Symbolic methods** and **Visual Program Induction**

Brown University, *Undergraduate Teaching Assistant*

Providence, RI | January 2021 - May 2022

- Computer Graphics (**C++ : Qt**) Fall 2022
 - Experience with **Docker**, **Qt**, and **CMake**
- Deep Learning (**Python : Tensorflow**) Spring 2022
- Introduction to Computer Systems (**C**, **x86 Assembly**) Fall 2021
- Object Oriented Programming (**Java**) Spring 2021

Openprise, *DevOps Software Engineering Intern*

Carlsbad, CA | April – August 2021

- Ensured product QA by enhancing the central testing framework
- Containerized testing framework with **Docker**

COMMUNITY EXPERIENCE

Brown University, *President of Brown Jazz Jams*

Providence, RI | September 2021 - May 2023

- Organizer and founder of Brown Jazz Jams, a group dedicated to organizing biweekly jazz jams on campus. I lead a small team coordinating logistics and outreach.

Big Brothers Big Sisters of America, *Youth Mentor*

Cambridge, MA | July 2024 - Present

SKILLS

Technical Skills:

- Professional: Python, Pytorch, Git
- Proficient: C, C++, Docker

Statement of Purpose

Interests

Tucked away in a corner of the Boston Museum of Fine Arts is a brass bicycle adorned by aluminum bananas hanging from its frame. “Untitled” by Subodh Gupta represents a common sight in rural South India: a hawker selling bananas from a bicycle. The beauty of this piece for me is its curatorial placement. Most if not all of the thousand-year-old objects on display alongside Gupta’s piece are either religious in nature or owned by wealthy patrons who derived some form of status from the object. They provide limited insight into the daily lives of ancient cultures, as they only represent a subsection of life from the region and time period. Gupta’s piece and its placement within the gallery are emblematic of a broader approach in archival studies – one which addresses the silences of the archives, or information not included “whether by chance, circumstance, or deliberate omission”.¹

I am broadly interested in generative models, 3D vision, computer graphics, and the digital humanities. Philosophically I am interested in the tension between what we consider real and what we consider fake. On the technical side I am interested in synthetic data, physically informed generative models, and combining data-driven neural methods with physical simulation and procedural systems. I am also generally interested in neuro-symbolic modeling and how to bring the strengths of neural and symbolic representations together. I want the freedom, time, and independence from corporate interests a PhD program provides to pursue these research directions, and I want to develop into an independent researcher who can create and pursue their own research agenda.

Synthetic data. Digital reality represents only a subsection of reality. The current focus on data-hungry machine learning algorithms obscures this problem behind a race for more data, all from the same cultural canon. Creating large datasets is also expensive, labor intensive, and runs into a host of labor or copyright issues. Synthetic data is an interesting alternative that can both satisfy the needs of limited data problems and address dataset bias.

One way to use synthetic data is to retrain a generative model on its own outputs. This approach however has its own unique challenges with mode-collapse.² For 3D vision tasks, procedural systems can generate 3D environments with annotations that are difficult to acquire in real life such as depth, semantic labels, and geometry. They struggle however with the sim-to-real gap as they lack the variability and realism of the natural world. Recent progress in text conditional image generation models opens up the possibility of generating diverse and realistic synthetic image data, but they are hard to control and do not come with the same guarantees, and annotations, that a procedural non-learned system comes with. A physically-based generative model that comes with the same guarantees a traditional physical simulator comes with such as multi-view consistency and physical realism has the potential to address current limitations of synthetic data.

Cultural heritage. The application of generative models and machine learning in cultural heritage reconstruction and preservation is unexplored territory due to a whole host of concerns. But even if the true nature of a historic place or object is epistemically unknown, generating those details can raise interesting questions about authenticity, fabrication, and authorship for people today. What degree of our knowledge of the past comes from hallucinated or fabricated

¹ Eun Seo Jo and Timnit Gebru. “Lessons from archives: strategies for collecting sociocultural data in machine learning”. In: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency (2019). url: <https://dl.acm.org/doi/10.1145/3351095.3372829>.

² Nate Gillman et al. “Self-Correcting Self-Consuming Loops for Generative Model Training”. In: Proceedings of the 41st International Conference on Machine Learning. Vol. 235. PMLR, 2024, pp. 15646–15677.

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information? What changes when we reconstruct a historic place or object through a modern lens? For people and regions of the world whose heritage has been omitted by history, reconstructing different versions of it can also act as a form of restorative justice.

Interpretable networks. I am also interested in neuro-symbolic modeling and mechanistic interpretability. How/can you map the internal computations of a neural network to semantic and understandable structures such as programs? What applications does this have in other scientific fields? What concepts do generative models know and how do they know them?

Experience

In undergrad I worked with Professor Daniel Ritchie and his student Doctor Kai Wang on indoor scene synthesis: learning to automatically furnish and complete rooms. We focused on autoregressive scene synthesis systems that place objects one at a time. Empirical observations of next object location distributions produced by previous data-driven systems^{3 4} revealed their tendency to become mode-collapsed or incomplete with respect to a rule a human might write. They overfit to particular object placements scene during training. I worked on a system that addresses this problem.

Functional constraints which explicitly encode placement rules tend to not become mode-collapsed. For example, a functional constraint specifying attachment against a wall cannot bifurcate into the individual placement locations such a rule might have been learned from. I designed and implemented a Domain Specific Language (DSL) based on functional constraints whose programs when given a partial scene and object to place produce a mask representing all the possible places the object can go.

I also implemented a transformer-based generative model which writes these programs automatically from a given partial scene and query object. This transformer model uses a new attention mechanism I implemented that allows it to attend to inter-object relationships better than the original attention mechanism. Available 3D scene data contain no “ground truth” programs which we can train said model on so I introduced an iterative self training scheme inspired by prior work in unsupervised visual program inference⁵ that improves the performance of our system. We formalized the empirical observations mentioned previously into a new evaluation metric and showed how our system beats previous methods on this metric.

After graduation I left academia to work as a research developer at Vision Systems Inc. I worked on the IARPA WRIVA program whose aim is to produce software that reconstructs 3D scenes from imperfect imagery. I contributed to the 3D scene reconstruction and rendering part of the system which takes in calibrated camera information and renders novel views.

Match

I would be most interested in working with Aleksander Holynski, Carl Vondrick, and Richard Zemel. Professor Holynski’s work on generative priors for reconstruction is relevant to my interests. Professor Vondrick’s work on learning from unlabeled data and interpretable neuro-symbolic models such as ViperGPT also overlaps with my interests. Professor Zemel’s

³ Despoina Paschalidou et al. “ATISS: Autoregressive Transformers for Indoor SceneSynthesis”. In: Advances in Neural Information Processing Systems (NeurIPS).2021.

⁴ Daniel Ritchie, Kai Wang, and Yu-An Lin. “Fast and Flexible Indoor Scene Synthesis via Deep Convolutional Generative Models”. In: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2018), pp. 6175–6183.

⁵ R. Kenny Jones, Homer Walke, and Daniel Ritchie. “PLAD: Learning to Infer Shape Programs with Pseudo-Labels and Approximate Distributions”. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2022).

Fall 2024
Columbia University
Adrian Chang

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interest in algorithmic fairness, computer vision, and machine learning is relevant to my interests.