

I am a final-year medical student with a strong passion for computer science. I aspire to research the working mechanisms, robustness, and interpretability of machine learning models and, as a long-term goal, to improve and solve problems in the real world. Consistent with this goal, I have worked on several research studies disentangling the neurodynamics of the brain, demystifying medical image translation models, and proving one meta-learning algorithm to be contrastive learning.

My passion for computer science led me to improve medical issues with machine learning. I took machine learning online courses offered by Andrew Ng in my first semester in medical school. I was deeply impressed by how scientists modeled a complex neuron using a simple mathematical model and intrigued by the delicate design of backpropagation. Afterward, I self-learned Linear Algebra to understand lectures about principal components analysis and support vector machines and Data Structure and Algorithms to program more efficiently. In my first-year medical internship, I spent much time in the hospital, thereby uncovering many unaddressed and unmet medical needs. Devoted to the field of machine learning since freshman year, I implemented several data-driven solutions, such as ICU monitoring, ECG detection, or cross-modality medical image translation, to these problems. However, I realized that there was a large gap between experiment and practice. Moreover, I could not dispel the doubt as to who is responsible for the false positive/negative and bias and how one can evaluate and tackle the responsibility of these models. These questions drove me to take a gap year and advance my studies in the Enriched Vision Applications Lab (EVA Lab), hosted by **Associate Professor Wei-Chen Chiu** (National Yang Ming Chiao Tung University, NYCU).

I was fortunate to be co-advised by **Doctor Pin-Yu Chen (MIT-IBM Watson AI Lab)**. Aware of the scarcity of available clinical data, I focused on MAML, one widely implemented meta-learning algorithm, and was captivated by its bi-level optimization scheme. Yet, I found concurrent theoretical and empirical explanations did not confront the core issue of why MAML makes models generalizable. Thus, I dedicated myself to explaining the working mechanism of MAML. I first visualized the loss landscape of meta-trained models. I tried to relate to multitasking learning, but they did not receive valuable insight. Afterward, I turned to a more theoretical aspect. I asked myself whether and how the support and query data interact during the bi-level optimization process. I approached the solution by assuming a simplified loss function. This led to the discovery that, when setting the weight of the linear heads to zero, the bi-level optimization procedure essentially implements a supervised contrastive learning objective. Moreover, my derivation revealed two potential interference terms implicit inside MAML. By removing them, the models converge faster, and the empirical performance notably increased. Currently, our work is being **reviewed by ICLR 2022**. Our work not only disclosed the intimate relationship between gradient-based meta-learning algorithms and contrastive learning but also implied that any algorithms adopting a min-min bi-level optimization scheme (e.g., Entropy-SGD) is implicitly performing contrastive learning.