We are collecting data on a large scale.

Certain applications can be modeled using physics. But for most tasks, there are very few hypotheses for how to model them. So, we generally give a model a large amount of data for autonomous learning. To make matters somewhat worse, supervised learning techniques require labels for such voluminous data, which are highly expensive to gather because they involve human evaluation.

For this reason, my research interests lie in learning from the least amount of data possible, i.e., active learning.

I started my interest in research during my undergrad at Purdue. There, I worked with Professor Suresh Jagannathan and his team on a reinforcement learning (RL) project to research a new algorithm to make RL model training efficient and safe. The solution has two levels: a high-level planner that creates a plan for the agent to complete the desired task, and a low-level controller that executes the planner's plan. The controller might deviate from the plan, and therefore, a Lyapunov neural network is employed to guarantee that an agent does not encounter an unsafe state. The ultimate goal of this project was to embed this model into a robot that can navigate a map without bumping into walls or obstacles.

In this project, I was involved in writing the code for the high-level planner, running the hyperparameters, simulating experiments, collecting data, and benchmarking. With our algorithm, out of 10,000 experiments, less than 30 simulations violated safety constraints. Our paper was accepted at a workshop in AAAI, and I presented this work at the Purdue University Fall Research Expo.

Next, in my Master's program at UIUC, I continued with reinforcement learning – this time, more on the theoretical side. I worked with Professor Hanghang Tong and his team to develop an active, supervised RLHF-bandit training algorithm that is not only efficient resource- and label-wise, but also combines the benefits of exploitation and exploration. Usually in bandit problems, the data is transformed into a long vector[1]. This means that we need more space to store data (which can be a problem with big datasets) and the networks would also have many parameters to learn. In this work, we work on the original input data, and use a simple neural network of 2 layers. As mentioned earlier, this is also a label-efficient method because we employ active learning. The labels come from human experts.

We provide two methods for stream-based and pool-based active learning. In the streaming setting, we decide on-the-fly whether or not to query a point. We calculate an exploitation-exploration score for each label, and if the difference between the score of the most optimal label and the second most optimal label is small enough, we query for the point and retrain the model. In the pool-based setting, in each of the R rounds, we create a distribution of the exploitation-exploration scores, sample b points from it, query those and update the models.

I had a bigger part in this project, as I am a joint first author on this paper. I implemented all the algorithms, experimented/researched different strategies that will make our algorithm better, decided

[1] A v-dimensional vector would transform to a kv-dimensional vector where k is the number of classes. The label is also transformed into a vector of k of zeros and the label value is determined by a '1' in the index of the label.

and researched the baselines, performed all the experiments, performed hyperparameter tuning, and wrote the 'Experiments' section of the paper.

A second project I've taken on continues my interest in active learning. Again, with Professor Hanghang Tong, I am leading a project on graph anomaly detection. We are developing an algorithm that will not only be able to learn the general pattern of anomalies but can also adapt to new kinds of data. In the industry, new kinds of anomalies can pop up every day. Instead of retraining a bulky model every so often, engineers can train a bulky model on all the existing data and keep retraining a smaller and more lightweight model to adapt to newer kinds of anomalies. Since this algorithm is label-efficient, we aim to calculate a confidence score and soft labels that will help us choose the most informative points. We have come up with a way to extract the most information out of the labeled data points. Anomalies are not just defined by the values of their features, but also the neighborhood structure they belong to. We aim to learn these structures via contrastive learning. Finally, we model this as a bilevel optimization problem in which each level learns each of the two components of this algorithm (a bulky model that will learn general patterns, and a lightweight classifier).

At `UniversityName`, I plan to continue my interests exploring the different applications and techniques of active learning.

`Talk about three research works from this university and elaborate on ways you can take that work forward.`

Conclusion. I want to contribute to making AI learn better models from less data with the bright minds at `UniversityName`.