Project Webpage:
http://andrew.cmu.edu/~tyj

Project Details:
For my project I will be pursuing next semester, I will be working with Changliu Liu, an assistant professor in the Robotics Institute. Any questions I may have may also be directed to Tianhao Wei, a grad student working with Professor Liu. The main topic of my project is human-robot interaction, particularly in a collaborative sense. I will focus on the task of human trajectory prediction.

As demands for human-robot collaboration increase across different domains like industry, health care, education, etc., the need for an efficient method of customizing such robots grows more apparent. If robots are meticulously designed to perform a single specific task, then a new task in a new environment will require a complete reprogramming, and may even require the underlying hardware to be changed. Obviously, this is very expensive and suboptimal, so efficient customization is the first big key to improving on these collaborative robots, or co-robots.

Not only is efficiency important in the design of robots, but safe operation is also essential to consider to prevent potentially harmful interactions between the human and the robot. A proposed method for maintaining a safe collaborative environment is to incorporate human motion prediction into the robot’s decision-making. Accurate human motion prediction will allow robots to plan their trajectories according to how the human is likely to move. This, however, is a very difficult problem in many ways, as different people behave differently, especially in different tasks. Thus, human motion prediction will occupy one portion of the overall pipeline of the co-robot system.

Another large part of the pipeline involves the robot’s skill learning, including everything from learning the tasks it needs to perform to adapting to the human’s movements and planning its trajectory in real time. It is very difficult to pre-program robots to perform every single task imaginable. So, work to be done in this area will involve two main steps: an initial stage of encoding, where skills shared universally across all tasks are learned by the robots, and an on-site stage of learning, where the specific task is taught to the robot. A proposed method of doing this is via human demonstration, where the robot observes two humans performing the task collaboratively, and mimics the human behavior.

My project will focus specifically on high fidelity behavior prediction of intelligent agents, building on previous research on the Modified Extended Kalman Filter with Exponential Moving Average and Dynamic Multi-Epoch strategy (MEKF\textsubscript{EMA-DME}). In particular, I will investigate whether or not parameter adaptation using Bayesian optimization is a feasible approach for designing the architecture for models trained on the task of human trajectory prediction. Any findings will likely be generalizable to supervised models trained on any tasks.

Impact:
There are many benefits to developing robots that can learn to safely collaborate with humans. As mentioned previously, typical robots as of now require a very involved, expert approach to encoding instructions for the tasks they are designed to perform. Forming this two step pipeline of human motion prediction and robot skill learning will lead to much easier, more efficient ways of teaching robots to perform varying tasks in varying environments efficiently with humans,
which will ultimately cut down on production costs and manual labor required to simply manufacture these robots.

**Previous Literature:**
The tasks that I will focus on for this project largely lie in the first portion of the pipeline, involving the human motion prediction. The first step of this process would be to gather examples of humans performing certain tasks. With this data, the next step is to train a prediction model on it. Abuduweili et al. introduced a new technique, called the Modified Extended Kalman Filter with Exponential Moving Average and Dynamic Multi-Epoch strategy (MEKF\textsubscript{EMA-DME}), to train the prediction model [1]. Also, Zhou et al. introduced a new technique for hyperparameter adaptation in an online setting [2]. I may be able to adapt their technique for the purposes of this project.

If time permits, work may also be done in the second portion of the pipeline, involving the robot’s skill learning. The first step of this process would be to present the robot with an initial demonstration of the task to perform. One approach for having the robot learn from this demonstration would be through model-agnostic meta-learning, which Finn et al. has shown to work very well on few-shot learning problems [3]. The act of demonstrating a task to a robot is, in nature, a one-shot learning task, so meta-learning would be very applicable to this scenario. In fact, Yu et al. has shown that model-agnostic meta-learning can be used to allow robots to effectively reproduce tasks they observe [4]. Gupta et al. also introduced a method for imitation learning combined with reinforcement learning, which succeeds in learning long-horizon tasks [5].

**Project Goals:**
To evaluate the success of the project, user studies will be conducted to measure the efficacy of the robot in collaborating with a human on a specific task. The efficiency and accuracy of the robot will be measured as an objective metric for how well it performs, and the humans’ satisfaction with the robot will be measured as a subjective metric for how well it performs.

To evaluate the success of the project, the loss of the predicted trajectory will be observed on a model with hand-picked hyperparameters, as well as on a model with adapted hyperparameters. The losses will be compared, and hopefully the results will provide evidence that hyperparameter tuning improves human trajectory prediction.

100% Goal: If all goes as expected, by the end of this semester, I will ideally have been able to evaluate the effectiveness of using hyperparameter adaptation as a method for choosing the optimal set of hyperparameters with which to train a model on the task of human trajectory prediction. If results are positive, I will be able to prove the method’s effectiveness. If not, I will have been able to investigate other forms of hyperparameter adaptation to lead to better results.

75% Goal: If things go more slowly than expected, by the end of this semester, I will have collected new data to train the model with, and I will at least have been able to run the baseline model with hand-picked hyperparameters on the new data. I will then have implemented hyperparameter adaptation in its simplest form. In this case, it is probable that I will not have been able to significantly modify the strategy to notably improve the results, but I will be able to either verify or disprove the effectiveness of such a method.

125% Goal: If things go faster than expected, by the end of next semester, I will have done everything in the 100% goal. I will also potentially look into implementing MEKF\textsubscript{EMA-DME} as an offline optimizer. A further reach would be to work even more in the online adaptation portion of
the project, where techniques such as meta-learning may be researched to see whether or not it may lead to improvements in the adaptation efficiency on new subjects.

Milestones:
1st Technical Milestone for 15-300: By the end of this semester, I hope to have gained a deeper understanding of the techniques that will be used next semester. In particular, I will look into reading about and understanding the methodology of meta-learning, as well as understanding various methods that are typically used for one-shot learning.

Bi-weekly Milestones for 15-400:
January 27th: Work on developing an understanding of the technology that is being used, such as how the input video data is being represented. Setting up my laptop for the project.
February 10th: Further develop an understanding of the existing code used, in particular the MEKF_{EMA-DME} code.
February 24th: Collect new data for the purpose of training the model. Begin to work on implementing hyperparameter adaptation.
March 16th: Continue implementing hyperparameter adaptation, testing its efficacy on the newly collected dataset.
March 30th: If the method works well on the newly collected dataset, begin to test hyperparameter adaptation on the pre-existing datasets.
April 13th: Modify method to optimize both space and time efficiency. If time permits, experiment with modifying MEKF_{EMA-DME} for offline adaptation.
April 27th: Continue testing the results, making modifications if necessary. Finalize the project.

Resources Needed:
To conduct the study, I will need Python, with common machine learning packages installed. I do already have these packages installed. It is also possible that a system with GPUs will be highly preferred for faster training. My laptop does not have a GPU, so I will see if the lab has a server which does utilize GPUs that I can SSH into. I will also need to figure out what software is necessary to interface with the robot, as I likely do not currently have the software installed.

References: