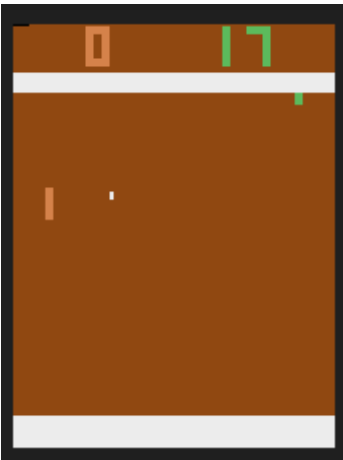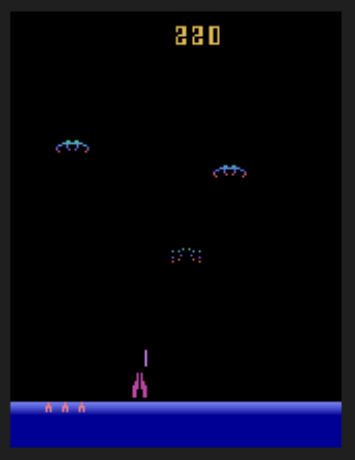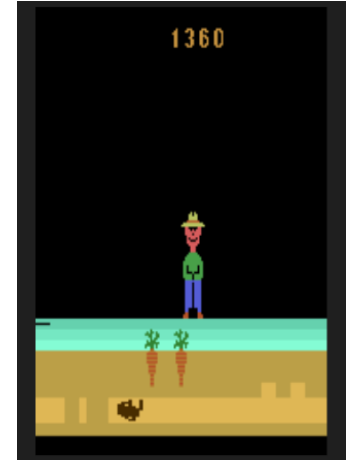The first time I felt like I did something interesting in vision-based learning problems was when I developed a CNN-based flower predictor using ImageNet models. It's basically the "Hello World" for using keras in vision tasks, but when my computer was accurately guessing what flower I'm looking at, it felt like I had conquered the world – and the surprising thing was, I didn't even have to make the effort to build the model from ground up.

That was my introduction to the concept of Transfer Learning and the notion of transferability. This simple idea had engrossed my mind – we can take a DNN model that works well on a similar problem and retrain it to solve our problem. I was simply opening a storage locker where the best of scholars have kept their knowledge, and I was using their knowledge to accomplish a task I wished to achieve. For me as a beginner, this was a grand discovery – and the use cases were simply boundless.

From then on, I strove to dive deeper into advanced machine learning concepts such as NLP, Reinforcement Learning and GANs. I explored the use of simple GRU and LSTM networks to execute sentiment analysis, and the abilities of GANs based models to produce pictures that looked almost like the original. However, the next milestone in my journey was reached when, inspired by the DeepMind paper on human-level gameplay on Atari games (Mnih, et al., 2015), I tried creating some of my own RL agents. With a lot of excitement and motivation, I connected my computer to Google Cloud and tried many different ways to obtain some decent gameplay from my agents. After many days of work, the results looked surprisingly good:

|  | ```
14996 loss:3.63552INFO:absl:
            NumberOfEpisodes = 46
            EnvironmentSteps = 60004
            AverageReturn = 1382.0
            AverageEpisodeLength = 1436.0999755859375
15994 loss:4.01065INFO:absl:
            NumberOfEpisodes = 50
            EnvironmentSteps = 64004
            AverageReturn = 1228.0
            AverageEpisodeLength = 1372.4000244140625
``` |
|  | ```
297999 loss:0.00056INFO:absl:
            NumberOfEpisodes = 514
            EnvironmentSteps = 1192004
            AverageReturn = 20.200000762939453
            AverageEpisodeLength = 1843.699951171875
298993 loss:0.00048INFO:absl:
            NumberOfEpisodes = 517
            EnvironmentSteps = 1196004
            AverageReturn = 20.600000381469727
            AverageEpisodeLength = 1785.199951171875
``` |

```
43992 loss:1.21686INFO:absl:
                NumberOfEpisodes = 272
                EnvironmentSteps = 176004
                AverageReturn = 268.5
                AverageEpisodeLength = 835.5999755859375
44995 loss:0.87877INFO:absl:
                NumberOfEpisodes = 279
                EnvironmentSteps = 180004
                AverageReturn = 229.5
```



```
296996 loss:1.923502INFO:absl:
                NumberOfEpisodes = 732
                EnvironmentSteps = 1188004
                AverageReturn = 3028.0
                AverageEpisodeLength = 1890.5
297998 loss:7.128001INFO:absl:
                NumberOfEpisodes = 734
                EnvironmentSteps = 1192004
                AverageReturn = 2504.0
                AverageEpisodeLength = 1698.199951171875
298994 loss:3.146576INFO:absl:
                NumberOfEpisodes = 736
                EnvironmentSteps = 1196004
                AverageReturn = 3102.0
                AverageEpisodeLength = 1880.800048828125
```

For minimal compute power and a good amount of training, these were pretty amazing. I made some GIFs where I could witness my agent playing the game, and I was astounded by the fact that, with a little guidance, I was able to make something like this possible. Back home, the largest exposure to smart technology we have are smartphones, and even with that most people usually struggle. 10 years ago, the smartest piece of technology for me was Google, something that reached into the clouds and brought forth any piece of knowledge I wanted. Therefore, being able to create an agent that could perform on a human level on a remote computer sitting in some part of US, and doing all that from the comfort of my home, was a huge milestone for me. I felt exposed to the true power of technology, and I was witnessing the true potential of RL.

These experiences have made me very passionate about Transfer Learning and Reinforcement Learning, especially in the domains of Robotics and Vision. My long-term goal is to pursue research in these fields, and develop means to explore and ensure transferability of models across domains, and also to develop systems that improve performance of reinforcement learning models in operating domains.

As a result, I am interested in the prospect of working with Dr. Gregory Hager, who has made great contributions in the study of accessing transferability of ML-based systems by using metadata to produce a context-space that is most relevant to the output of the loss, which would allow us to predict the performance of a trained model in the operating domain (O'Brien, Goble, Hager, & Bukowski, 2020). Currently, Professor Hager is working on extracting context spaces from embeddings. This study involves determining the dimensions that most impact the loss function and how the change in embeddings would affect performance in new domains, and that is a line of research that I would like to pursue. Moreover, in the past work, topics such as ML Dependability, Task Unpredictability and Harmful Undependability were explored for networks trained to perform simulated robot manipulation tasks in novel operating conditions using test results, and a future research avenue on this topic involves extending this work to partially observed domains, which are opportunities I am very interested in exploring with Dr. Hager.

I am also intrigued by Dr. Nassir Navab's research in simulation-based reinforcement learning for real-world ultrasound probe navigation, where he trained an A2C deep RL agent on real-time observations to navigate an ultrasound probe to the longitudinal view of a vessel, essentially using RL to perform ultrasound plane searching for vascular anatomies (Bi, et al., 2022). Transferability from simulation environment to real scenarios was achieved on this problem through the use of UNet, which segmented the vessel area from the ultrasound images before using it as state representation. I found this to be a brilliant application of RL to solve real-world medical problems, and I believe this idea is extendible to a whole multitude of other anatomies. Consequently, I find the possibility of working with Dr. Navab very appealing.

I have also found Dr. Chien-Ming Huang's work on learning group-aware policies for robot navigation very compelling. For this work, RL was used to learn a policy that allowed a robot to navigate to a desired goal while maintaining social norms and avoiding collision with groups of pedestrians (Gao, et al., 2022). I find this work to be an integral contribution to the assimilation of robots into human workspaces and general human environments. Future research is possible in this domain through the use of imitation learning using observations of humans navigating groups of pedestrians, and that is a research avenue I would like to explore with Dr. Huang, if provided the opportunity.

I am thrilled at the prospect of pursuing my PhD at John's Hopkins University. At JHU, the work of several faculty members is very well-aligned with my research interests, and on top of that I would be part of a very rich community filled with excellent opportunities and brilliant peers. It is the perfect place for me to develop myself. That is why, I believe JHU is the gate to my future career in research.

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