ONLINE DEEP LEARNING FOR OBJECT RECOGNITION ON A MOBILE ROBOT

Watch as our robot, Bandit, recognizes objects in the room completely on its own! Train it, show it a new object, and Bandit will correctly identify it!

INTRODUCTION

Our project investigates the struggle to train machines to retain old information while learning new data, despite modern advancements in Neural Networks.

We are using Bandit, a Fetch mobile robot, to gather images of objects to classify. Our goal is to train Bandit to predict the class of new objects with an accuracy of 80% or higher.

BACKGROUND

We hypothesized that if we adjust the network model to value weights compatible with old and new data, our network will have increased efficiency adding data to its current collection.

This is based on the concept of Elastic Weight Consolidation (EWC), a state of the art online learning algorithm.

Our intelligent agent is dynamically learning about its environment, making our model applicable in a range of environment where humans need assistance. Our system will shine in settings such as: labs, factories, offices, kitchens, etc.

Oregon State University

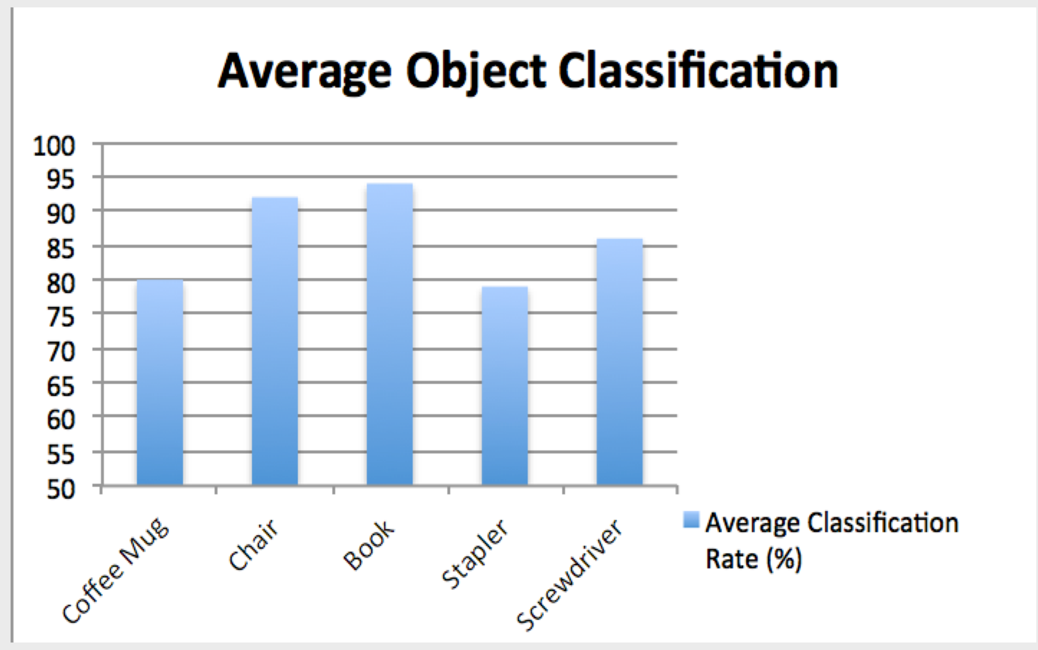
PROGRAM DESCRIPTION

Our team implemented a software pipeline to manage interacting programs in our project. After Bandit gathers images, a collection of scripts perform data preparation, convolutional neural network (CNN) training, and object class prediction. The network is updated sequentially with new input from Bandit over time to achieve online learning.

Our classification system is initialized with general object classes to keep its predictions broad. With online learning, over time the network overfits itself to the objects it is exposed to and learns their individual features, such as logos, shapes, colors, and orientations.

With this in mind, our data set contains a variety of objects with different key features and dimensions. Individual objects have distinguishing traits Bandit can recognize, and consist of staplers, mugs, chairs, screwdrivers, and books to mimic realistic use cases.

RESULTS



94%:

The average classification success rate of our model trained on the 5 object classes, 14% higher than our starting goal!

2 hours:

The average training time of our model with 500 images on an Nvidia GeForce GTX 970 GPU.

CONCLUSION

As we predicted, our model is able to classify objects with an 80+% success rate.

It is capable of identifying an object's overarching class and is able to differentiate between old and new objects.

Through online learning, the model is also able to learn new traits about previously seen objects over time.

This technology was the fundamental concept that allowed our model to efficiently and dynamically add image data to the network's current knowledge.

We demonstrated a template use case in which placeholder objects were introduced and learned over time, and are now interested in expanding these concepts to real environments.

Team From Left to Right
Miles McCall mccallm@oregonstate.edu
Julian Weisbord weisborj@oregonstate.edu
Michael Rodriguez rodrigmi@oregonstate.edu

Client
Dr. Bill Smart smartw@oregonstate.edu

Organization
Oregon State University Personal Robotics Lab

Acknowledgements
Special thanks to Chris Eriksen for helping to guide the project and assist throughout.

Who am I?
- Mobile Robot
- Intelligent Agent
- Good Boy