Image Classification by Reinforcement Learning With Two-State Q-Learning

ECSE 626 Final Project by Evelyn Hubbard

Original Paper by: Abdul Mueed Hafiz [1]

December 1, 2024

Presentation Outline

1. Paper Introduction and Context
2. Image Classification and Active Learning Background
3. Model Architecture
4. Reinforcement Learning Background
5. Hafiz's Two-State Q-Learning Algorithm
6. Original Paper Results
7. ECSE 626 Project Contributions and Results
8. Paper Critiques and Suggestions

Introduction

- Image classification: traditionally solved by supervised learning techniques.
- Reinforcement learning (RL): method for learning optimal policies in sequential decision-making problems.
- Active vision: acquires multiple observati ons and **selects** parameters of the observation process

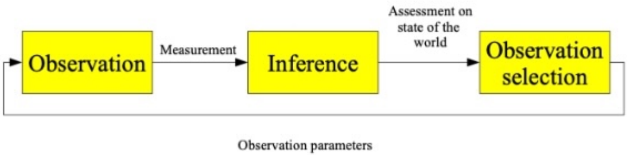

Figure: Active Vision Loop, adapted from [2]

Hafiz’s 2022 Paper Context

- Deep Q-networks integrated RL with deep learning and demonstrated Q-learning’s applicability to high-dimensional data [3]
- Connection with computer vision was prevalent from around 2015 to 2020 (ex: landmark detection) [3]
- Motivation for Hafiz’s paper [1]:
    - Image resolution selection
    - Reconstruction of digits using feature maps
    - Earlier RL and image classification work with the goal of learning effective transformations on images (pre-classification)

Novelty of Hafiz's Paper

Hafiz's paper proposed two new ideas [1]:

1. New action: rotation
2. Two-state Q-learning algorithm: instead of using the image as the state, the state is "better" or "worse" depending on the standard deviation of classification predictions after an action is taken

Model Architecture

Three model components:

1. Feature extracting CNN (predicts a class for a given image)
2. Classifying structure (predicts a class for a feature map)
3. Reinforcement learning algorithm (two-state Q-Learning on feature-maps to improve classification)

Deep Learning:

- The CNN is composed of a pre-trained base (ResNet50 ImageNet) and custom fine-tuned layers.
- The secondary classifier (an NN or SVM) is trained on the feature maps for a training set of images.

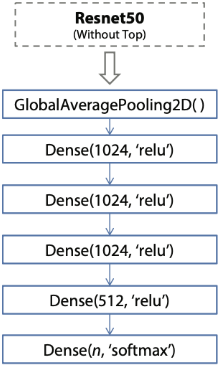

Figure: Custom NN layers added to ResNet50 from [1]

Model Architecture

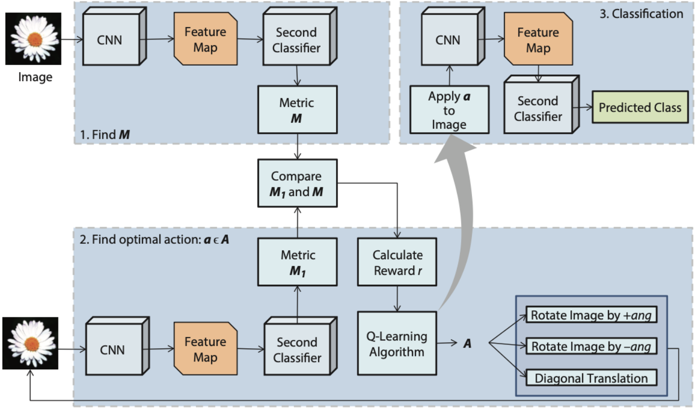

Figure: Model Architecture[1]

Reinforcement Learning

Reinforcement Learning

- Markov Chain and trainsition kernel....
- reward function
- Reinforcement learning is a type of machine learning that involves an agent learning to make decisions by interacting with an environment.
- The agent receives rewards or penalties based on its actions, and its goal is to learn a policy that maximizes its cumulative reward.
- Q-learning is a popular reinforcement learning algorithm that learns a Q-function, which estimates the expected reward of taking an action in a given state.
- The Q-function is used to determine the best action

Structural Results of Reinforcement Learning

Two-State Q-Learning

- The two-state Q-learning algorithm uses a predictor to approximate the state of the environment.
- The predictor is trained to predict the next state of the environment given the current state and action.
- The Q-function is then learned using the predicted state instead of the true state.
- This reduces the state-action space and allows the agent to learn a policy more efficiently.

Connection to Model

Paper's Results

My Contributions and Results

Paper Critiques

Suggestions

Discussion

Conclusion

Comparing the approximation schemes:

- Sliding window method: computationally efficient, insensitive to initialization, requires a strong form of filter stability
- Quantized state space method: works under weaker stability conditions, sensitive to initialization, computationally more complex

Future research could extend these methods to scenarios with noisy channels, channels with feedback, or systems with infinite state/action spaces.

References:

[1] A. M. Hafiz, “Image Classification by Reinforcement Learning With Two-State Q-Learning,” in Handbook of Intelligent Computing and Optimization for Sustainable Development, John Wiley and Sons, Ltd, 2022, pp. 171-181. doi: 10.1002/9781119792642.ch9.
[2] C. Laporte, ”Active Vision for Doctors in the Making,” presented in *ECSE-626: Statistical Computer Vision*, Fall 2024, McGill University, Montreal, QC, Canada.
[3] N. Le, V. S. Rathour, K. Yamazaki, K. Luu, and M. Savvides, “Deep reinforcement learning in computer vision: a comprehensive survey,” Artif Intell Rev, vol. 55, no. 4, pp. 2733–2819, Apr. 2022, doi: 10.1007/s10462-021-10061-9.

Thank you!