Measures of Generalisation for Deep Reinforcement Learning Models

Literature Review - Group 28

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Structure of the Presentation

- The importance of generalisation and why it is difficult to achieve
- Introduction to Deep Reinforcement Learning
- Measuring generalisability
  - Empirical analysis
  - Theoretical analysis
    - Formal methods
- Discussion of the state of the art
- Directions for further research
- Q&A

Generalisation

Generalisation matters

- Adaptability of a model to a new environment.
- Hallmark of intelligent systems (Lake et al. 2017).
- Essential for safety critical tasks, driving

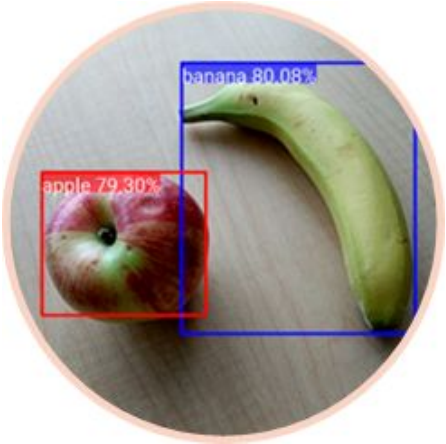
Generalisation is hard

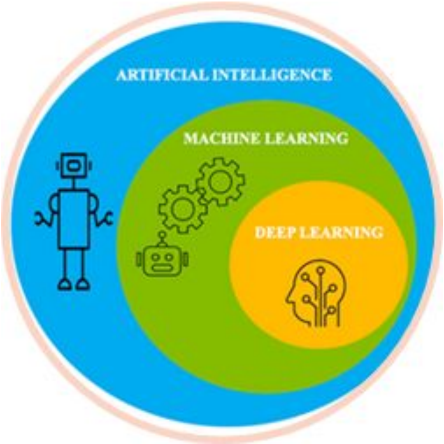
- Sit!
- Deep learning performance is highly susceptible to small changes in the environment

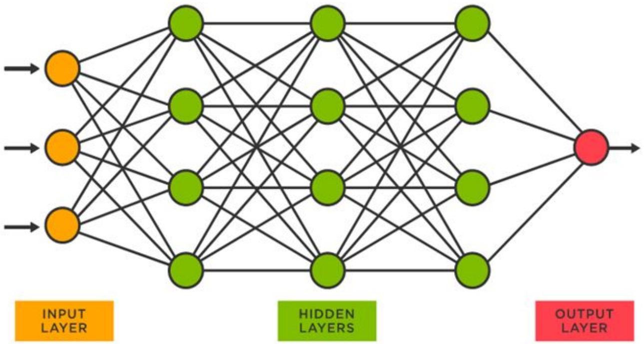
Deep Reinforcement Learning

Deep Learning

- Models mimic the neural structure of the brain.
- Excel on high dimensionality, sparse datasets.
- Example use cases
  - Image recognition
  - Translation

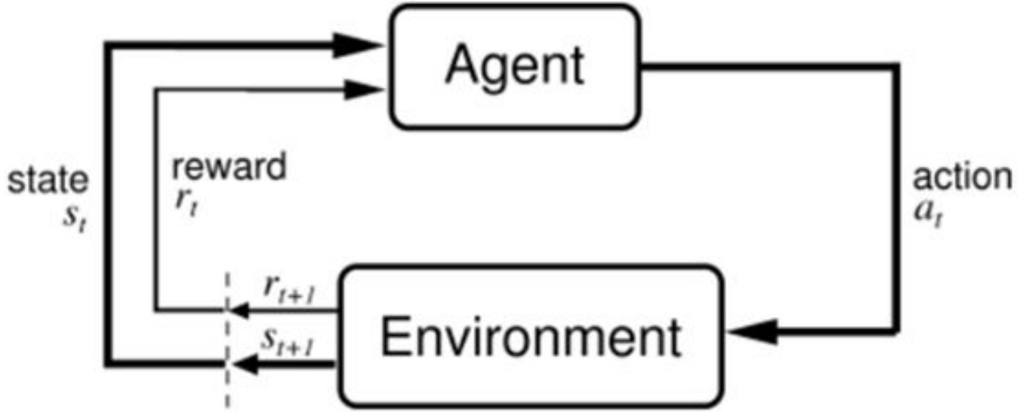






Reinforcement Learning

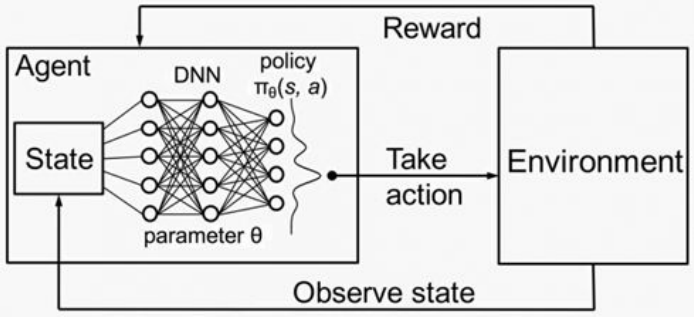
- The agent performs an action based on the state of the environment.
- The action updates the state of the environment and solicits some level of reward from the environment.
- The new state of the environment and level of reward form the new input to the model



Applications of reinforcement learning

Deep Reinforcement Learning

- Uses deep learning models to find rewarding policies.
- Better handles the complexity of high dimensionality state spaces.
- Deep RL models have mastered Go (Silver et al. 2016) and StarCraft II (Vinyals et al. 2019)
- Expectations for DRL in the future are very high; Silver et al. (2021) claim that reward maximisation is sufficient for intelligence.



Measuring Generalisation

Overview

- Empirical methods - test a given model on new data
- Theoretical methods - predict the performance of a model given the training data
- Reachability analysis - given a trained model, what behaviour is possible

Empirical Methods

- Procedurally generating new levels of a game, eg. CoinRun (Cobbe et al. 2019).
- Variations in the parameters of an environment (Packer et al. 2019).

A procedurally generated level in CoinRun

Empirical Methods - Discussion

- Test environments are overly simplistic, and include only similar tasks (e.g. varying one element of the environment).
- Empirical tests do not explain why models are successful at generalising.
- Danger of researchers overfitting to test environments (cf. ImageNet).
- Test environments are model agnostic.

Theoretical Measures - Generalisation Bounds

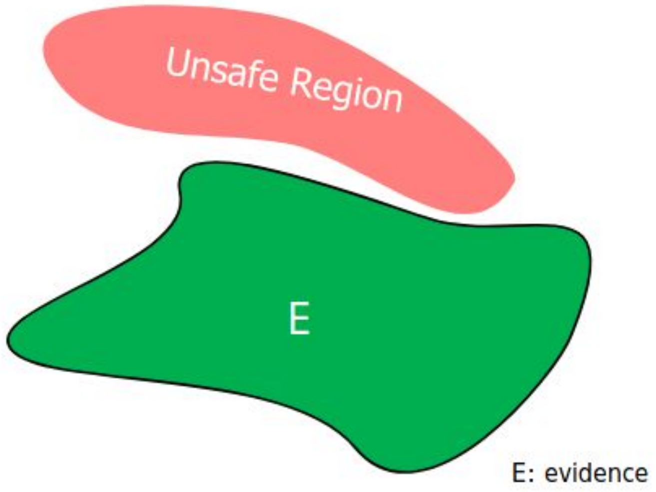
- Attempt to establish a bound for the generalisation gap of a model on a dataset.
- DL models generally can achieve zero training error - eg. random ImageNet categories
- Prove a bound on the generalisation gap based on the training data and model (not test data) - hard to get narrow bounds

Theoretical Measures - Correlated measures

- Correlate generalizability with measures, eg. sharpness of minima
- Correlation != causation, need careful experiments

Reachability Analysis

- Provide guarantees on model behaviour.
- Given a range of inputs, what are the possible outputs of a model.
- Derive properties such as the robustness of the model.
- Useful for understanding behaviour where testing is not appropriate.



Protecting against unsafe behaviour (DARPA)

Reachability Analysis - Discussion

- Scaling is a problem - currently <60k nodes.
- Determining the unsafe zone and adjusting model behaviour.
- Heuristics like robustness need interpretation.

Analysis

Findings

- No consensus on measures for generalisability in the literature.
- Interpretation of the results is difficult.
- Lower research intensity vs. model building.

Recommendations

- Establish a standard empirical test set
  - Hold back test data to prevent overfitting
  - Increase complexity and realism as models improve
- Provide more education on these methods
  - How to interpret results of theoretical methods
  - Applicability of empirical results to new environments

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