# Learning Generalized Heuristics Using Deep Neural Networks

Julia Nakhleh
Director: Siddharth Srivastava

AAIR
Autonomous Agents and Intelligent Robots
Arizona State University

# Introduction

- Classical planning
  - AI domain concerned with decision-making in real-world tasks (e.g. doing laundry)
  - Computationally difficult due to size and complexity of environments
    - Slight increase in number of objects → significant slowdown
  - PSPACE-complete even when environment is deterministic and fully-observable (Bylander 1994)
- Generalized planning
  - Construction of plans that solve multiple problem instances
  - Identify common structures between problems; execute same solution with minor modifications
  - Improves efficiency on new planning instances

# Introduction (cont.)

- Our approach: generalized planning + deep learning
    - Given a planning problem instance and a generalized representation of a state, our network learns a Generalized Reactive Policy (GRP) that predicts the best action to take from that state
    - Network also predicts the generalized *role* of the object within the environment
- Tested on two domains: blocks world and logistics
    - Results in both domains indicate success, although network accuracy is lower in the more complex logistic domain

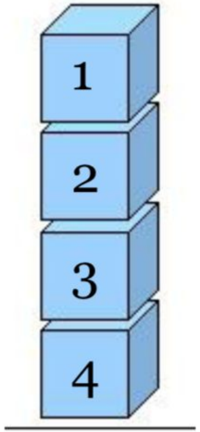
# Related Work

- Application of learning techniques to classical planning interfaces
  - Martin and Geffner (2004): learn generalized policies using concept languages
  - Rosman and Ramamoorthy (2012): use reinforcement learning to learn action priors
- Deep Neural Networks
  - State-of-the-art in image classification (Krizhevsky, Sutskever, and Hinton 2012) and NLP (Sutskever, Vinyals, and Le 2014)
  - Learn heuristic functions (Ernandes and Gori 2004)
  - Learn an Alpha Go policy (Silver et al. 2017)
  - Learn a GRP and a planning heuristic based on images of a successful Sokoban trace (Groshev et al. 2017)

# State Abstraction

- Given a domain, a goal formula, and a set of initial states, a *generalized planner* computes a generalized plan that solves all of the initial states
    - Initial states may be from different state spaces, but must be from the same domain
- Srivastava, Immerman and Zilberstein (2011) propose a method of state abstraction that compactly represents concrete, unbound states
    - Summary elements: may represent multiple physical entities
    - Non-summary elements: represent only one physical entity

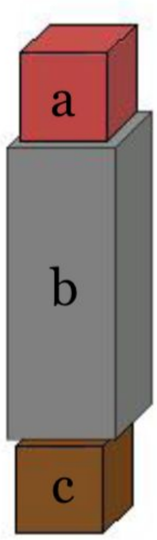
# Non-abstract state




| on | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1 | 0 | 1 | 0 | 0 |
| 2 | 0 | 0 | 1 | 0 |
| 3 | 0 | 0 | 0 | 1 |
| 4 | 0 | 0 | 0 | 0 |

Non-abstracted representation of a blocks world state (Srivastava 2011).

# Abstract state

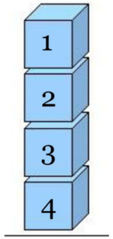



| *on* | a | b | c |
|---|---|---|---|
| a | 0 | ½ | 0 |
| b | 0 | ½ | ½ |
| c | 0 | 0 | 0 |

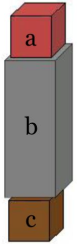
Abstract representation of a blocks world state (Srivastava 2011).

# State Abstraction (cont.)

- Three-valued logic
  - 1 = true, 0 = false, ½ = unknown/undefined
- Role = the set of unary predicates an object satisfies
  - Roles correspond to summary elements
  - a = {*clear*}, c = {*onTable*}, b = {} (i.e. ¬*clear* ^ ¬*onTable*)
  - Summary element *a* corresponds to block 1, *c* to block 4, and *b* to blocks 2 and 3



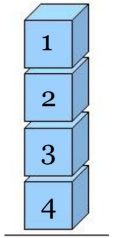

| *on* | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1 | 0 | 1 | 0 | 0 |
| 2 | 0 | 0 | 1 | 0 |
| 3 | 0 | 0 | 0 | 1 |
| 4 | 0 | 0 | 0 | 0 |



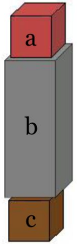

| *on* | a | b | c |
|---|---|---|---|
| a | 0 | ½ | 0 |
| b | 0 | ½ | ½ |
| c | 0 | 0 | 0 |

# State Abstraction (cont.)

- Binary relationships become imprecise
  - For example, (on a b) is valued as ½ because not all of the concrete elements within a are directly on top of all of the concrete elements within b




| *on* | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **1** | 0 | 1 | 0 | 0 |
| **2** | 0 | 0 | 1 | 0 |
| **3** | 0 | 0 | 0 | 1 |
| **4** | 0 | 0 | 0 | 0 |




| *on* | a | b | c |
|---|---|---|---|
| **a** | 0 | ½ | 0 |
| **b** | 0 | ½ | ½ |
| **c** | 0 | 0 | 0 |

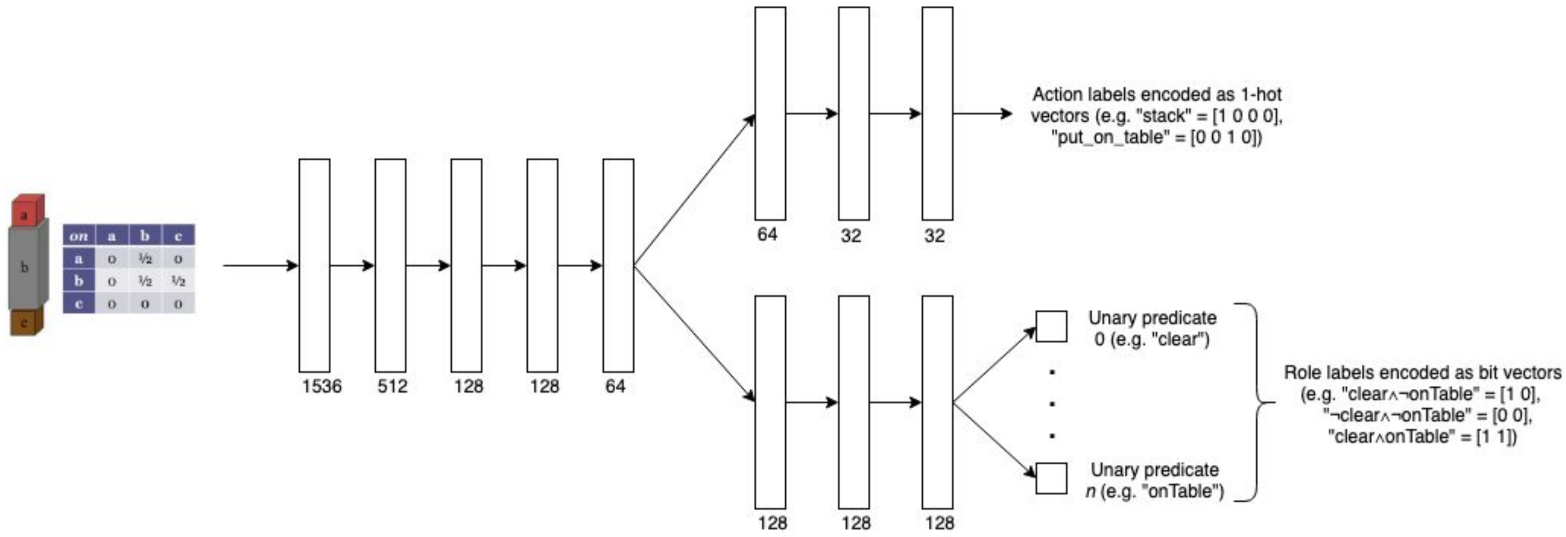
# Neural Network Input/Output

- Input format: matrix representing abstracted state
  - Dimensions: $n_r$ x $n_r$ x $n_b$
  - $n_r$ = number of possible roles, $n_b$ = number of binary predicates in domain
  - We used abstracted states as input because they allow an unbounded number of objects to be represented compactly
    - Problems of different sizes are represented with same dimensions (necessary for NN)
- Label (i.e. output) format: vectors representing (i) correct action to take from a given state and (ii) role of object being acted upon
  - Actions: 1-hot encoded vector of length $n_a$ (number of actions in domain)
  - Roles: bit-encoded vector of length $n_u$ (number of unary predicates in domain)

# Neural Network Design

- 11 + *n* fully-connected square layers, where *n* is the number of unary predicates in the domain
  - 5 shared layers
  - 3 action layers
  - 3 roles layers
  - *n* 1-bit layers, each of which indicates whether a unary predicate is present (1) or absent (0) in the role
- Loss taken as softmax over loss on each unary predicate layer + loss on action predictions

# Neural Network Design (cont.)



# Domains Tested

- Blocks world
  - Robot must stack/unstack a set of wooden blocks on a table
  - Only one block can be moved on a time
  - Start: 2-10 blocks in random configuration of ≥1 towers
  - Goal: all blocks on table
- Logistic
  - Truck(s) must load, unload, and deliver crates between a set of fixed locations
    - Our version uses 1 truck, 5 locations, and 15-20 crates
    - Truck assumed to have infinite capacity
  - Start: all crates are randomly distributed among locations
  - Goal: crates are evenly distributed among locations

# Experiments

- Fast-Forward (FF) Planner (Hoffman and Nebel 2001)
  - Given initial configuration, goal configuration, and the rules of the planning domain, FF computes sequence of actions and intermediate states from start to goal
  - [state i: “unstack 1”] → [state ii: “place_on_table 4”] → …
  - NN data (abstract states) and labels (action and concrete object role) are manually extracted from returned FF Plan
- NN training data generated by running FF on large problem sets
  - Blocks world: 6000 training problems, 1000 test problems
    - ~35,000 training instances, ~5,762 test instances
  - Logistic:  500 training problems, 100 test problems
    - ~30,000 training instances, ~6,000 test instances

# Results - Blocks World

- Proof of concept
- Immediately achieves 100% accuracy on both action and role predictions
- All loss in range [-2e-07, 3e-06] → effectively ~0.00 loss
- Extremely high accuracy due to simplicity of problem
    - In our version, only 2-10 blocks
    - Since goal is “all blocks on table”, the network only ever learns action “unstack” and role “clear”
    - Still a promising result

# Results - Logistics

- Accuracy of action predictions reaches 96%
- Accuracy of role predictions hovers around 75%
  - Partially due to the way that current locations of crates within trucks are encoded within the domain

# Logistics - sample predictions


Correct action: unloadAtL5 crate5
Network prediction: unloadAtL5 crate5

Role of crate 5: ["crate", "atL3", "destinationL5"]
Network prediction: ["crate"]

# Logistics - sample predictions


Correct action: unloadAtL5 crate10
Network prediction: unloadAtL5 crate10

Role of crate 10: ["crate", "atL3", "destinationL5"]
Network prediction: ["crate"]

# Logistics - sample predictions


Correct action: unloadAtL4 crate14
Network prediction: unloadAtL4 crate14

Role of crate 14: ["crate", "atL1", "destinationL4"]
Network prediction: ["crate"]

# Logistics - sample predictions


Correct action: moveToL5 truck1
Network prediction: moveToL5 truck1

Role of truck1: ["truck", "atL4"]
Network prediction: ["truck", "atL4"]

# Future Work

- Experiment with different loss functions (sum of squares, etc.)
  - Weight action loss vs. role loss
- Test on different domains and problem types
  - Blocks world: different goal configurations, block colors
  - Logistics: multiple trucks, limited truck capacity
- Convolutional Neural Network (CNN)
  - Particularly useful if input is represented as an image rather than a matrix
- Test effectiveness of learned GRP as a planning heuristic
  - Compare performance against best-first search

# Conclusion

- Neural network indicates a promising ability to learn based on abstract state representations
    - More difficult in more complex domains
    - We hypothesize that with further tuning, and with slight modifications to the logistics domain, the network's accuracy on the logistics domain can be significantly improved
- Further testing is needed to compare effectiveness of learned GRP as a planning heuristic

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