Deep Learning for Cost-Optimal Planning: Task-Dependent Planner Selection

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Setting

- (General) Domain-independent planning
- Problem: no single best planner for all domains

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- Problem: no single best planner for all domains
- Combine planners in portfolios

  [Gerevini et al. 2011, Helmert et al. 2011, Vallati 2012, Seipp et al. 2012/2015, Seipp et al. 2014, Núñez et al. 2015, Cenamor et al. 2016]
- Most prominent in satisficing planning/learning settings

Problem

Motivation

- Can we construct a good portfolio for optimal planning?
- Online portfolios: solve classification task for (single) planner selection
- Good technique for classifcation tasks: deep learning

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Contributions:

- Representation of planning tasks consumable by deep learning
- Proper evaluation of techniques used in Delfi1, winner of last optimal IPC
- Discussion of encountered issues

Outline

1. Introduction
2. Planning Task Representation
3. Learning
4. Discussion

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Planning Tasks

Given in a logic-based description (PDDL):

```
(:action pick-up
 :parameters (?x)
 :precondition
  (and (clear ?x) (ontable ?x) (handempty))
 :effect
  (and (not (ontable ?x))
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       (not (handempty))
       (holding ?x))
)
```

Representing Planning Tasks

Goal

Use image convolution for classification.

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How to obtain representative images?

- SAT/CSP: convert textual problem description into images
- Here: focus on structure of planning tasks

Representative Graphs

Abstract structure graph: compact encoding

- Nodes for components of the PDDL description (predicates, objects, parameters, etc.)
- Edges to connect components if one is part of another

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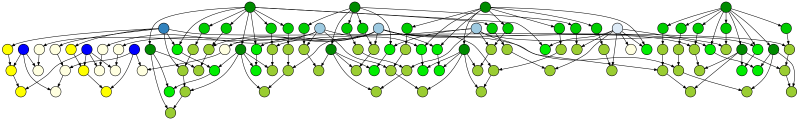

Representative Images

Conversion of graphs into images:

- Encode adjacency matrix as black&white image
- Turn into grayscale by clustering pixels
- Resize to fixed size

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- Goal: predict which planner(s) from the portfolio solve a given task
- Use simple convolutional neural networks

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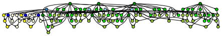

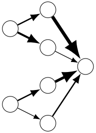

Performance Representation

Multilabel classification:

- Binary: predict whether planners solve given task
- Discretized runtime (3 intervals): predict in which interval planners belong

Multilabel regression: predict . . .

- Raw runtime
- Normalized runtime

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Delfi1: binary

Planner Collections

- Fast Downward-based planners from Delfi1
- Those from Delfi1 + additional planners from IPC 2018
- Minimal subset of above to cover training data

Benchmarks

- Training set: domains from IPCs prior 2018
- Test set: domains from IPC 2018

Training Data Separation

- Two training data splits: random vs. domain-preserving
  random split
- Validation vs. no validation

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Choices of Delfi1:

- Hand-crafted domain-preserving split
- No validation for final training (only for hyper parameter optimization)

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48 settings, train 10 models for each

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Further Observations:

- Mostly consistent planner selection within domains
- Not as strong as Delfi1 itself

Issues

- Somewhat large variance across different models
- Data is not independently identically distributed (i.i.d.)

Potential Future Work

- More sophisticated networks, graph conversion
- Use graphs convolution
- Automatically generate tasks with a certain structure:
  $\rightarrow$ i.i.d. distribution of tasks?

The End

Thank you for listening!

Poster tonight 7:00 – 8:30 pm: PRS 5097