Learning in Depth-First Search

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Introduction

- Dynamic Programming provides a convenient and unified framework for studying many state models used in AI, but no algorithms for handling large state spaces

- Heuristic search methods can handle large state spaces but have no common foundation; e.g. IDA*, AO*, αβ-pruning, ...

- In this work, we combine DP and heuristic search into an algorithmic framework, called **Learning in Depth-First Search**, that is both general and effective

- LDFS combine iterative depth-first searches with learning in the sense of Korf’s Learning RTA* (LRTA*)

- On **Deterministic** problems, LDFS reduces to IDA* with Transposition Tables, on **Game Tree** problems to MTD (MTD = αβ-pruning with null windows + memory; Plaat et al. 1996); it also applies to other models like AND/OR, MDPs, games with chance nodes, etc
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Deterministic Models

Understood in terms of:

- a discrete and finite state space $S$,
- an initial state $s_0 \in S$,
- a non-empty set of terminal states $S_T \subseteq S$,
- actions $A(s) \subseteq A$ applicable in each non-terminal state,
- a function that maps states and actions into states $f(a, s) \in S$, and
- action costs $c(a, s)$ for non-terminal states $s$. 
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**Solutions**: sequences $a_0, \ldots, a_n$ of actions that “transform” $s_0$ into a terminal state
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**Preferred:** IDA* is a linear space algorithm, memory can be exploited with a Transposition Table
Game Trees

Understood in terms of:

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**Algorithms:** Minimax, $\alpha\beta$-pruning, MTD, ...
AND/OR Models

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**Optimal:** if minimizes $V^\pi(s_0)$

**Algorithms:** AO*, CFC/REV, ...
Unification via Dynamic Programming

DP deals with models given in terms of:

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- terminal costs $c_T(s)$ for terminal states.
**Solutions to DP**

Understood in terms of solutions $V^*$ for Bellman equations:

$$V(s) = \begin{cases} 
  c_T(s) & \text{if } s \text{ is terminal} \\
  \min_{a \in A(s)} Q_V(a, s) & \text{otherwise}
\end{cases}$$

where $Q_V(a, s)$ stands for the cost-to-go value defined as:

- $c(a, s) + V(s')$, $s' \in F(a, s)$ for **DETERMINISTIC**,
- $c(a, s) + \max_{s' \in F(a, s)} V(s')$ for **Max AND/OR (NON-DET-MAX)**,
- $c(a, s) + \sum_{s' \in F(a, s)} V(s')$ for **Add AND/OR (NON-DET-ADD)**,
- $c(a, s) + \sum_{s' \in F(a, s)} P_a(s'|s)V(s')$ for **MDP**,
- $\max_{s' \in F(a, s)} V(s')$ for **GAME TREE**.
Solutions to DP

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where $Q_V(a, s)$ stands for the cost-to-go value defined as:

- $c(a, s) + V(s')$, $s' \in F(a, s)$ for deterministic,
- $c(a, s) + \max_{s' \in F(a, s)} V(s')$ for Max AND/OR (NON-DET-MAX),
- $c(a, s) + \sum_{s' \in F(a, s)} V(s')$ for Add AND/OR (NON-DET-ADD),
- $c(a, s) + \sum_{s' \in F(a, s)} P_a(s'|s)V(s')$ for MDP,
- $\max_{s' \in F(a, s)} V(s')$ for GAME TREE.

**Solutions**: a partial function $\pi$ that maps states into actions such that it is closed with respect to $s_0$.
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- $c(a, s) + \max_{s' \in F(a, s)} V(s')$ for Max AND/OR (Non-Det-Max),
- $c(a, s) + \sum_{s' \in F(a, s)} V(s')$ for Add AND/OR (Non-Det-Add),
- $c(a, s) + \sum_{s' \in F(a, s)} P_a(s'|s)V(s')$ for MDP,
- $\max_{s' \in F(a, s)} V(s')$ for Game Tree.

**Solutions**: a partial function $\pi$ that maps states into actions such that it is closed with respect to $s_0$

**Optimal**: if $V^\pi(s_0) = V^*(s_0)$
Solutions to DP

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$$V(s) = \begin{cases} 
c_T(s) & \text{if } s \text{ is terminal} 
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where $Q_{V}(a, s)$ stands for the cost-to-go value defined as:

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**Solutions:** a partial function $\pi$ that maps states into actions such that it is closed with respect to $s_0$

**Optimal:** if $V^\pi(s_0) = V^*(s_0)$

**Algorithms:** Value Iteration, Policy Iteration, ...
Learning in Depth-First Search

LDFS-DRIVER(s₀)
begin
  repeat solved := LDFS(s₀) until solved
  return (V, π)
end

LDFS(s)
begin
  if s is SOLVED or terminal then
    if s is terminal then V(s) := c_T(s)
    Mark s as SOLVED
    return true
  
  flag := false
  foreach a ∈ A(s) do
    if Q_V(a, s) > V(s) then continue
    flag := true
    foreach s' ∈ F(a, s) do
      flag := LDFS(s') & [Q_V(a, s) ≤ V(s)]
      if ¬flag then break
    if flag then break
  
  if flag then
    π(s) := a
    Mark s as SOLVED
  else
    V(s) := min_a∈A(s) Q_V(a, s)
  return flag
end
Properties of LDFS

- LDFS computes $\pi^*$ for all models the initial $V$ is admissible (i.e. $V \leq V^*$)
Properties of LDFS

- LDFS computes $\pi^*$ for **all models** the initial $V$ is admissible (i.e. $V \leq V^*$)

- For **DETERMINISTIC** models and *monotone $V$*,

  $$\text{LDFS} = \text{IDA}^* + \text{Transposition Tables}$$
Bounded LDFS

B-LDFS(s, bound)
begin
    if s is terminal or V(s) ≥ bound then
        if s is terminal then V(s) := U(s) := c_T(s)
        return true
    flag := false
    foreach a ∈ A(s) do
        if Q_V(a, s) > bound then continue
        flag := true
        foreach s' ∈ F(a, s) do
            nb := bound − c(a, s)
            flag := B-LDFS(s', nb) & [Q_V(a, s) ≤ bound]
            if ¬flag then break
        if flag then break
    if flag then
        π(s) := a
        U(s) := bound
    else
        V(s) := min_a∈A(s) Q_V(a, s)
end

B-LDFS-DRIVER(s_0)
begin
    repeat B-LDFS(s_0, V(s_0)) until V(s_0) ≥ U(s_0)
    return (V, π)
end
Properties of Bounded LDFS

• For GAME TREE models and $V = -\infty$,

\[
\text{Bounded LDFS} = \text{MTD}(\infty)
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Properties of Bounded LDFS

- For \textit{GAME TREE} models and $V = -\infty$, 
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- For \textit{ADDITIVE} models, 
  \[ \text{LDFS} = \text{Bounded LDFS} \]
Properties of Bounded LDFS

- For **GAME TREE** models and $V = -\infty$, 

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- For **ADDITIVE** models, 

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- For **MAX** models, 

  \[ \text{LDFS} \neq \text{Bounded LDFS} \]
Properties of Bounded LDFS

- For Game Tree models and $V = -\infty$,

$$\text{Bounded LDFS} = \text{MTD}(-\infty)$$

- For Additive models,

$$\text{LDFS} = \text{Bounded LDFS}$$

- For Max models,

$$\text{LDFS} \neq \text{Bounded LDFS}$$

- LDFS (like VI, AO*, min-max LRTA*, etc) computes optimal solutions graphs where each node is an optimal solution subgraph (global optimality); over Max models, however, this isn’t needed, and is wasteful.
Global vs Local Optimality

Global Optimality

Local Optimality
Empirical Evaluation: Domains

• **Coins:** There are $N$ coins including a counterfeit coin that is either lighter or heavier than the others, and a 2-pan balance. A strategy is needed for identifying the counterfeit coin, and whether it is heavier or lighter than the others. We experiment with $N = 10, 20, \ldots, 60$.

• **Diagnosis:** There are $N$ binary tests for finding out the true state of a system among $M$ different states. An instance is described by a binary matrix $T$ of size $M \times N$ such that $T_{ij} = 1$ iff test $j$ is positive when the state is $i$. The goal is to obtain a strategy for identifying the true state. We performed two classes of experiments: a first class with $N$ fixed to 10 and $M$ varying in $\{10, 20, \ldots, 60\}$, and a second class with $M$ fixed to 60 and $N$ varying in $\{10, 12, \ldots, 28\}$.

• **Rules:** We consider the derivation of atoms in acyclic rule systems with $N$ atoms, and at most $R$ rules per atom, and $M$ atoms per rule body. In the experiments $R = M = 50$ and $N$ is in $\{5000, 10000, \ldots, 20000\}$.

• **Mts:** A predator must catch a prey that moves non-deterministically to a non-blocked adjacent cell in a given random maze of size $N \times N$. At each time, the predator and prey move one position. Initially, the predator is in the upper left position and the prey in the bottom right position. The task is to obtain an optimal strategy for catching the prey. We consider $N = 15, 20, \ldots, 40$,.
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Empirical Evaluation: Results (3 Domains)
Conclusions

• DP formulations and heuristic search can be combined into a framework that reveals the similarities among different AI algorithms

• not only we were able to understand better previous algorithm, but to develop new more effective algorithms for Max models

• LDFS and Bounded LDFS can be thought as generalizations of IDA* for NON-DETERMINISTIC models, and, as the latter, it suffers some of its shortcomings

• We are currently working on methods to deal with them

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• LDFS and Bounded LDFS can be thought as generalizations of IDA* for NON-DETERMINISTIC models, and, as the latter, it suffers some of its shortcomings

• We are currently working on methods to deal with them

• Papers (available at [http://www.ldc.usb.ve/~bonet](http://www.ldc.usb.ve/~bonet)):