Artificial Intelligence

CS 165A

Apr 24, 2022

Instructor: Prof. Yu-Xiang Wang

→ Finish games and minimax search
→ Midterm review
Recap: Games and minimax search

• Perfect information, turn-based, Deterministic, zero-sum game

• Formulation as a search problem: MIN and MAX alternatively.

• Alpha/Beta Pruning of the Search Tree

• Early Cut-off search with an heuristic function
Today

• Finish games and adversarial search:
  – Playing against multiple opponents
  – Exploiting benign opponent with Expectimax

• Midterm review
Small Pacman Example

MAX nodes: under Agent’s control

\[ V(s) = \max_{s' \in \text{successors}(s)} V(s') \]

MIN nodes: under Opponent’s control

\[ V(s) = \min_{s' \in \text{successors}(s)} V(s') \]
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Coding Project 2

• PACMAN with ghosts

• You will generalize minimax search to multiple opponents in Q7
• You will exploit the benign opponents in Q8
Expectimax: Playing against a benign opponent

- Sometimes your opponents are not clever.
  - They behave randomly.
  - You can take advantage of that by modeling your opponent.

- Example of game of chance:
  - Slot machines
  - Tetris
Expectimax example

- Your opponent behave randomly with a given probability distribution,
- If you move left, your opponent will select actions with probability [0.5,0.5]
- If you move right, your opponent will select actions with [0.6,0.4]
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Note: pruning becomes tricky in expectimax… think about why.
Summary of game playing

- Minimax search
- Game tree
- Alpha-beta pruning
- Early stop with an evaluation function
- Expectimax
More reading / resources about game playing

• **Required reading:** AIMA 5.1-5.3

• **Stochastic game / Expectiminimax:** AIMA 5.5
  - Backgammon. TD-Gammon
  - Blackjack, Poker

• **Famous game AI:** Read AIMA Ch. 5 “Historical notes”
  - Deep blue
  - TD Gammon
  - AlphaGo / AlphaZero

• **AlphaGo:** [https://www.nature.com/articles/nature16961](https://www.nature.com/articles/nature16961)
About the upcoming midterm

• **Topics:** Cover up to A*-Search and HW2. (not including Games / Adversarial search)

• **Types of questions:**
  – True/False, MCQ, BayesNet reading, simple calculations / derivations. Similar to quiz questions in the lecture slides.

• **What am I testing you on:**
  – Test of basic concepts.
  – Test of simple mechanical calculations.
  – Test of your ability to “generalize”
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- **What am I testing you on:**
  - Test of basic concepts.
  - Test of simple mechanical calculations.
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- **Tough questions?** Don’t panic and try your best.
  - Bonus questions may not be difficult (some are), but you are expected to finish non-bonus questions first.
About the upcoming midterm

• **Date:** Next Tuesday in class

• **Duration:** 1 hour 15 minutes

• **Format:** Open book (but no digital devices)
  – No calculator needed.
How to prepare for the midterm?

• Read relevant chapters from AIMA

• Lecture videos from a previous year will be made available to you (on Piazza)
  – Mostly the same
  – Slight differences on the syllabus

• Try solving problems in the optional homeworks
  – HW0, HW1, HW2

• Participate in discussions on Piazza
Time to pause and take a look back!

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- **Machine Learning**
- **Probabilistic Reasoning**
- **Search**
- **Reinforcement Learning**
- **Logic**
- **Responsible AI**
Lecture 1: AI Overview & Agents

- AI for problem solving
- Rational agents
- Examples of AI in the real world
- Modelling-Inference-Learning Paradigm
New paradigm: Modeling-Inference-Learning
Structure of the course

Low-level intelligence

Reflex Agents
Classification / Regression
Bandits

Planning Agents
Search
game playing

High-level intelligence
Reasoning agents
Markov Decision Processes
Reinforcement Learning
Logic, knowledge base
Probabilistic inference

Machine Learning
Probabilistic Graphical Models / Deep Neural Networks

Generate

Discriminate
## Modeling-Learning-Inference Paradigm

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<th>Learning</th>
<th>Inference</th>
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<td>Classifier agent (Spam filter)</td>
<td>Feature engineering Hypothesis class</td>
<td>Minimize Error rate</td>
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<td>Probabilistic Inference agent (Sherlock)</td>
<td>Joint distribution Draw edges in BN Conditional independences</td>
<td>Fitting the CPTs to Data</td>
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<td>Search agents</td>
<td>State-Space-diagram</td>
<td>Environment given (learn edge weights) (Learn heuristics?)</td>
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### PEAS Description of Task Environment

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<th><strong>S</strong></th>
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<td>Classifier agent (Spam filter)</td>
<td>Error rate</td>
<td>New example arrives</td>
<td>Classify</td>
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<td>Error in the computed $P(Y</td>
<td>X)$</td>
<td>Joint distribution via PGM</td>
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<td>Search agents</td>
<td>Completeness, Optimality, Time / Space complexity</td>
<td>State-space diagram</td>
<td>Choose a sequence of operators</td>
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Lecture 2-4: Machine Learning

- Machine learning
  - Types of machine learning models
  - Focus on Supervised Learning ---- classifier agents.

- What is a feature vector?
  - Feature engineering, feature extraction

- Hypothesis class and free parameters
  - How many are there? How to evaluate a classifier?
  - Error? On training data or on new data?
  - Overfitting, underfitting?

- How to learn (optimize)?
  - Surrogate losses, Gradient Descent, SGD
Example of a feature vector of dimension 4

<table>
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<tr>
<th>Contains hyperlinks</th>
<th>Proportion of misspelled words</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>0.0375</td>
</tr>
<tr>
<td></td>
<td>80</td>
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</table>

Whether the contact list

Length of the message

Step 1 in Modelling Feature extractor:
Converting the object of interest to a vector of numerical values.
Example: Linear classifiers

• Score(x) = \( w_0 + w_1 \times 1(\text{hyperlinks}) + w_2 \times 1(\text{contact list}) + w_3 \times \text{misspelling} + w_4 \times \text{length} \)

• A linear classifier: \( h(x) = 1 \) if \( \text{Score}(x) > 0 \) and 0 otherwise.

• Question: What are the “free-parameters” in a linear classifier?
  – If we redefine \( \mathcal{Y} = \{-1, 1\} \)
  – A compact representation: \( h(x) = \text{sign}(\omega^T[1; x]) \)
Linear classifier

- Think geometrically

  - What is the set of all feature vectors that a particular linear classifier will classify as “Spam”?

    \[ \{ x \in \mathbb{R}^d \mid \text{sign}(w^T x) = 1 \} = \{ x \in \mathbb{R}^d \mid w^T x > 0 \} \]

  - What is the set of all classifiers that will classify a particular data point to be “Spam”?

    \[ \{ w \in \mathbb{R}^d \mid \text{sign}(w^T x) = 1 \} = \{ w \in \mathbb{R}^d \mid w^T x > 0 \} \]
Geometric view: Linear classifier are “half-spaces”!

\[ \{ x \mid w_0 + w_1 \cdot x_1 + w_2 \cdot x_2 + w_3 \cdot x_3 + w_4 \cdot x_4 > 0 \} \]

The set of all “emails” that will be classified as “Spams”.

- Proportion of misspelled words
- Length of the message
Just “relax”: relaxing a hard problem into an easier one

\[
\min_{w \in \mathbb{R}^d} \text{Error}(w) = \frac{1}{n} \sum_{i=1}^{n} 1(\text{sign}(w^T x_i) \neq y_i)
\]

\[
\min_{w \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^{n} \ell(w^T x_i, y_i).
\]
Loss functions and surrogate losses
Loss functions and surrogate losses

- 0-1 loss: \( 1(h_w(x) \neq y) \)
Loss functions and surrogate losses

• 0-1 loss: \( 1(h_w(x) \neq y) = 1(\text{sign}(S_w(x)) \neq y) \)
Loss functions and surrogate losses

- 0-1 loss: \(1(h_w(x) \neq y) = 1(\text{sign}(S_w(x)) \neq y)\)

- Square loss: \((y - S_w(x))^2\)
Loss functions and surrogate losses

- 0-1 loss: \(1(h_w(x) \neq y) = 1(\text{sign}(S_w(x)) \neq y)\)

- Square loss: \((y - S_w(x))^2\)

- Logistic loss: \(\log_2(1 + \exp(-y \cdot S_w(x)))\)
Loss functions and surrogate losses

- **0-1 loss:** \( 1(h_w(x) \neq y) = 1(\text{sign}(S_w(x)) \neq y) \)

- **Square loss:** \((y - S_w(x))^2\)

- **Logistic loss:** \(\log_2(1 + \exp(-y \cdot S_w(x)))\)

- **Hinge loss:** \(\max(0, 1 - y \cdot S_w(x))\)
Illustration of GD vs SGD

Observation: With the time gradient descent taking one step, SGD would have already moved many steps.
One natural stochastic gradient to consider in machine learning

- Recall that
  $$\min_{\theta \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^{n} \ell(\theta, (x_i, y_i))$$

- Pick a **single** data point $i$ uniformly at random
  
  - Use $\nabla_\theta \ell(\theta, (x_i, y_i))$

  - Show that this is an unbiased estimator!
Intuition of the SGD algorithm on the “Spam Filter” example

\[ \nabla \ell(w, (x_i, y_i)) = \frac{\exp(-y_i \cdot x_i^T w)}{1 + \exp(-y_i \cdot x_i^T w)} (-y_i x_i) \]

Scalar > 0:
\[ \approx 0 \text{ if the prediction is correct} \]
\[ \approx 1 \text{ otherwise} \]

Vector of dimension d:
provides the direction of the gradient

If we receive an example [1, 0, 0.0375, 80] like the one before.
And a label \( y = 1 \) saying that this is a spam.

How will the SGD update change the weight vector?

Then by moving \( w \) towards the negative gradient direction, we are changing the weight vector by increasing the weights. i.e., increasing the amount they contribute to the score function (if currently the classifier is making a mistake on this example)
Calculating the gradients of surrogate loss functions

- Example: Binary logistic loss
  \[
  y \in \{-1, 1\} \\
  l(w) = \log \left( \frac{1 + \exp(-y \cdot x^T w)}{1 + \exp(y \cdot x^T w)} \right)
  \]
  \[
  \nabla l(w) = \frac{\exp(y \cdot x^T w)}{[1 + \exp(-y \cdot x^T w)]} (y) x_i \\
  \rightarrow \\
  (y) x_i
  \]

- Example: Cross-entropy loss
  \[
  l(w) = \begin{cases} 
  y \cdot \log \frac{\exp(x^T w)}{1 + \exp(x^T w)} + (-y) \cdot \log \frac{1}{1 + \exp(x^T w)} 
  
  \end{cases}
  \]
  \[
  \nabla l(w) = -y \cdot \frac{(1 + \exp(x^T w)) \cdot \exp(-x^T w) \cdot (-x^T w) \cdot (-y) - 1 + \exp(x^T w)}{(1 + \exp(x^T w))^2}
  \]
  \[
  = -(y \cdot \exp(x^T w) \cdot (-x^T w) + (-y) \cdot \frac{1 + \exp(x^T w)}{1 + \exp(x^T w)} \cdot \exp(x^T w) \cdot x^T w)
  \]
Lecture 5-7: Probabilities and BayesNet

• Modelling the world with a joint probability distribution
  – Number of independent parameters?

• CPTs
  – Count number of independent numbers to represent a CPT

• Conditional, Marginal, Probabilistic Inference with Bayes Rule

• Read off conditional independences from the graph
  – d-separation
  – Bayes ball algorithm
  – Markov Blanket
Tradeoffs in our model choices

\[ O(N) \]

\[ O(e^N) \]

Fully Independent
\[ P(X_1, X_2, \ldots, X_N) = P(X_1) P(X_2) \cdots P(X_N) \]

Fully general
\[ P(X_1, X_2, \ldots, X_N) \]

Space / computation efficiency

Expressiveness

Idea:
1. Independent groups of variables?
2. Conditional independences?
How should we connect the nodes? (3 min discussion)

Burglary

Earthquake

Alarm

JohnCalls

MaryCalls

Links and CPTs?
What are the CPTs? What are their dimensions?

Question: How to fill values into these CPTs?
Ans: Specify by hands. Learn from data (e.g., MLE).
Big question: Is there a general way that we can answer questions about conditional independences by just inspecting the graphs?

- Turns out the answer is “Yes!”
d-separation in three canonical graphs

\[ X \perp Z \mid Y \]

“X and Z are d-separated by the observation of Y.”

\[ X \perp Z \mid Y \]

“X and Z are d-separated by the observation of Y.”

\[ X \perp Z \mid Y \]

“X and Z are d-separated by NOT observing Y nor any descendants of Y.”
The Ten Rules of Bayes Ball Algorithm
Lecture 7-9: Search

• Problem solving by search
  – Abstraction, problem formulation
  – State-space diagram
  – Count the number of states, number of actions.

• Search algorithms
  – General search strategy, data-structure used
  – Space / time complexity
  – Four evaluation criteria

• Heuristic search
  – When does it work?
Problem Formulation and Search

• Problem formulation
  – State-space description $< \{S\}, S_0, \{S_G\}, \{O\}, \{g\}>$
    • $S$: Possible states
    • $S_0$: Initial state of the agent
    • $S_G$: Goal state(s)
      – Or equivalently, a goal test $G(S)$
    • $O$: Operators $O: \{S\} \rightarrow \{S\}$
      – Describes the possible actions of the agent
    • $g$: Path cost function, assigns a cost to a path/action
  • At any given time, which possible action $O_i$ is best?
    – Depends on the goal, the path cost function, the future sequence of actions…..
• Agent’s strategy: Formulate, Search, and Execute
  – This is offline problem solving
More quizzes: PACMAN with static ghosts

- The goal is to eat all pellets as quickly as possible while staying alive. Eating the “Power pellet” will allow the pacman to eat the ghost.

- Think about how to formulate this problem.
State-Space Diagrams

• State-space description can be represented by a state-space diagram, which shows
  – States (incl. initial and goal)
  – Operators/actions (state transitions)
  – Path costs
State Space vs. Search Tree (cont.)

Search tree (partially expanded)
**General Search Algorithm**

- Uses a queue (a list) and a **queuing function** to implement a *search strategy*
  - *Queuing-Fn(queue, elements)* inserts a set of elements into the queue and determines the order of node expansion

```plaintext
function **GENERAL-SEARCH**(problem, QUEUING-FN) returns a solution or failure

nodes ← MAKE-QUEUE(MAKE-NODE(INITIAL-STATE[problem]))

loop do
  if nodes is empty then return failure
  node ← REMOVE-FRONT(nodes)
  if GOAL-TEST[problem] applied to STATE(node) succeeds then return node
  nodes ← QUEUING-FN(nodes, EXPAND(node, OPERATORS[problem]))

end
```
Summary table of uninformed search

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<tr>
<th>Criteria</th>
<th>BFS</th>
<th>Uniform-cost</th>
<th>DFS</th>
<th>Depth-limited</th>
<th>IDS</th>
<th>Bidirectional</th>
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<tr>
<td>Complete?</td>
<td>Yes#</td>
<td>Yes#&amp;</td>
<td>No</td>
<td>No</td>
<td>Yes#</td>
<td>Yes#+</td>
</tr>
<tr>
<td>Time</td>
<td>O(b^d)</td>
<td>O(b^{1+[C/\epsilon]})</td>
<td>O(b^m)</td>
<td>O(b')</td>
<td>O(b^d)</td>
<td>O(b^{d/2})</td>
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<td>Space</td>
<td>O(b^d)</td>
<td>O(b^{1+[C/\epsilon]})</td>
<td>O(bm)</td>
<td>O(bl)</td>
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<td>Optimal?</td>
<td>Yes$</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes$</td>
<td>Yes$+</td>
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*b*: Branching factor
*d*: Depth of the shallowest goal
*l*: Depth limit
*m*: Maximum depth of search tree
*e*: The lower bound of the step cost

#: Complete if *b* is finite
&: Complete if step cost >= *e*
$: Optimal if all step costs are identical
+: If both direction use BFS

(Section 3.4.6 in the AIMA book.)
Example

State space graph

Search tree

Queue

(A)
(B C)
(C D)
(D B D E)
(B D E)
(D E D)
(E D)
(D F)
(F)
( )
A* Example

\[ f(n) = g(n) + h(n) \]
A* Example

1. Know how to track the nodes in the frontier
2. Select which one to expand first.
What are some general principles behind AI?

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- **Machine Learning**
- **Probabilistic Reasoning**
- **Search**
- **Reinforcement Learning**
- **Logic**
- **Responsible AI**
Optimization perspective of AI
Optimization perspective of AI

• A rational agent \( \max_{a_1, \ldots, a_T} \text{Utility}(a_1, \ldots, a_T) \)

  – **Modelling tools**: Features / Hypothesis class, PGM, State-space abstraction, agent categorization
  – **Constraints**: Computation, Data, Storage
Optimization perspective of AI

• A rational agent
  \[
  \max_{a_1, \ldots, a_T} \text{Utility}(a_1, \ldots, a_T)
  \]
  
  – **Modelling tools:** Features / Hypothesis class, PGM, State-space abstraction, agent categorization
  
  – ** Constraints:** Computation, Data, Storage

• Discrete optimization
  \[
  \min_{p \in \text{Paths}} \text{Distance}(p)
  \]
  
  – **Algorithmic tool:** Search / Dynamic programming
Optimization perspective of AI

• A rational agent

\[
\max_{a_1, \ldots, a_T} \text{Utility}(a_1, \ldots, a_T)
\]

– **Modelling tools**: Features / Hypothesis class, PGM, State-space abstraction, agent categorization
– **Constraints**: Computation, Data, Storage

• Discrete optimization

\[
\min_{p \in \text{Paths}} \text{Distance}(p)
\]

– **Algorithmic tool**: Search / Dynamic programming

• Continuous optimization

\[
\min_{\theta \in \mathbb{R}^d} \text{TrainingError}(\theta)
\]

– **Algorithmic tool**: Gradient descent / Stochastic gradient descent
Different objectives to optimize in AI

• **PGM:**
  – MLE: Maximize the log-likelihood function
  – Classifier / decision: max the posterior distribution

• **Search and planning:**
  – Find valid solutions with smallest path cost.

• **Machine Learning**
  – (Regularized) Empirical Risk Minimization (ERM):
    \[
    \min_{\theta \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^{n} \ell(\theta, (x_i, y_i)) + \lambda r(\theta)
    \]
A lot of these problems are computationally / statistically hard, but so what?
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- Get help from human:
  - Use model
  - Use abstractions at the right level
  - Use features
  - Use heuristic functions
A lot of these problems are computationally/statistically hard, but so what?

• Get help from human:
  – Use model
  – Use abstractions at the right level
  – Use features
  – Use heuristic functions

• Get help from mathematics and computer science theory:
  – Solve an approx. solution
  – Approximate inference of a PGM
  – More iterations with less accuracy per SGD
  – A* Search
Good luck with your midterm!