CS 343 Overview and Conclusion

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• Please fill out the course survey

- Feedback to both instructors and TAs
- Positive and negative points are useful ullet
- form of participation

• Capture the Flag contest results!

Post on Piazza/Email your completion screenshot teaching staff as a

6 teams participated, 4 qualified

Rankings



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Rankings

4th place: ReinforcedChaos (Nalin Mahajan, Vineeth Bandi)



6 teams participated, 4 qualified

Rankings

3rd place: KentFoxes (Xuefei Zhao, Yuhan Zheng) 4th place: ReinforcedChaos (Nalin Mahajan, Vineeth Bandi)



SCORE: 0



6 teams participated, 4 qualified

Rankings

2nd place: EasiestDifficulty (Joseph Muffoletto)
3rd place: KentFoxes (Xuefei Zhao, Yuhan Zheng)
4th place: ReinforcedChaos (Nalin Mahajan, Vineeth Bandi)



6 teams participated, 4 qualified

Rankings

1st place: oranges (Ramya Prasad, Jennifer Suriadinata)
2nd place: EasiestDifficulty (Joseph Muffoletto)
3rd place: KentFoxes (Xuefei Zhao, Yuhan Zheng)
4th place: ReinforcedChaos (Nalin Mahajan, Vineeth Bandi)

Congratulations to All!



Overview of AI Topics

Search / Planning

Uninformed SearchMinimaxA* SearchExpectimaxCSPsMDPsLocal SearchClassic Planning

Machine Learning

Reinforcement Learning Probability Theory Bayes Nets HMMs Particle Filters Decision Diagrams

Naive Bayes Perceptrons Neural Networks Kernels Clustering

VPI



Overview of Machine Learning



Maximize Your Expected Utility



Constraint satisfaction: searching intelligently for legal solutions

8			4		6			7
						4		
	1					6	5	
5		9		3		7	8	
				7				
	4	8		2		1		3
	5	2					9	
		1						
3			9		2			5

How Do Al Systems Maximize Utility?

Example: Sudoku

Utility: Does the solution satisfy the rules / constraints?

Assumptions: We can write down the rules / constraints of the problem



Planning: reasoning with models

Example: Robot navigation

Utility: Path length, collisions, surfaces, energy, social factors

Assumptions: We have a model of the world and the effects of the agent's actions



Supervised Learning: learning from labeled examples

Example: Image classification **Utility:** Classification accuracy on images not seen during training

Assumptions: We have access to a (usually large) labeled data set



Unsupervised Learning: discovering patterns in unlabeled data

Example: Clustering species

Utility: "Best" explanation of data

Assumptions: Data points that should be clustered together are "close" together

Reinforcement Learning: learning from experience



Example: Robot walking

Utility: Time until fall, speed, energy efficiency

Assumptions: We can "reward" and "punish" good and bad performance, but don't know what the correct action at each step should be

Properties of task environment

- Fully observable vs. partially observable Single-agent vs. multi-agent Deterministic vs. stochastic
- Episodic vs. sequential
- Static vs. dynamic
- Discrete vs. continuous
- Known vs. unknown

Single agent vs. multi-agent

- Not multi-agent if other agents can be considered part of the environment
- Only considered to be multi-agent if the agents are maximizing a performance metric that depends on other agents' behavior
- Single agent example: Pacman with randomly moving ghosts
- Multi-agent example: Pacman with ghosts that use a planner to follow him

Single

Uninformed Search A* Search Local Search CSPs

Single / Multi Agent

Multi

Minimax

Expectimax

MDPs

Reinforcement Learning

Deterministic vs. stochastic

- Deterministic: next state of environment is completely determined by the current state and the action executed by the agent
- Stochastic: actions have probabilistic outcomes
- Strongly related to partial observability most apparent stochasticity results from partial observation of a deterministic system
- Example: Coin flip

Deterministic

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Minimax

Determinism

Stochastic

Expectimax

MDPs

Reinforcement Learning

Decision Diagrams

- Fully observable: agent's sensors give it access to complete state of the environment at all times
- Can be partially observable due to noisy and inaccurate sensors, or because parts of the state are simply missing from the sensor data
- Example: Perfect GPS vs noisy pose estimation
- Example: IKEA assembly while blindfolded

Almost everything in the real world is partially observable

Fully Observable

Minimax Uninformed Search Expectimax A* Search Local Search MDPs CSPs Reinforcement Learning

Observability

Partially Observable

POMDPs Bayes Nets HMMs

Decision Diagrams

- Agent's state of knowledge about the "rules of the game" / "laws of physics"
- Known environment: the outcomes for all actions are given • Unknown: agent has to learn how it works to make good decisions
- Possible to be partially observable but known (solitaire) Possible to be fully observable but unknown (video game)

Model of the World

Known

Uninformed SearchMinimaxA* SearchExpectimaxLocal SearchMDPsCSPsValue IterationClassic PlanningDecision Diagrams

Unknown

Q Learning Learning parameters of Bayes Net

LARG's Research Highlights

Discussion Question

- In the next 100 years
- Later or Never

When will AI reach human-level intelligence?

- In the next 10 years
- In the next 50 years

Discussion Question

When will AI reach human-level intelligence?

- In the next 10 years
- In the next 50 years
- In the next 100 years
- Later or Never



First class before discussion

1. When will In the next 10 y

In the next 50 y

In the next 100

Later or Never

1. When will AI reach human-level intelligence?

) years	(5) 3%
) years	(58) 35%
00 years	(65) 39%
er	(38) 23%

1. When will AI reach human-level intelligence?

In the next 10 years	(1) 1%
In the next 50 years	(39) 23%
In the next 100 years	(75) 45%
Later or Never	(53) 32%

Al reach human-level intelligence?				
years	(3) 3%			
years	(27) 28%			
) years	(37) 39%			
	(28) 29%			

First class after discussion

Do you care if our "descendants" are human?

How do we develop AI to its fullest while keeping the human spirit unique to Homo Sapiens, or do we even care about this distinction? (Cole Kauppinen)

- We have come a long way! Thank you!
- course, especially during this special time!
- responses, in-class discussions, and assignments!
- and let us know!

• We are very proud that you have made it to the end of this demanding

• We are impressed by your ingenuity and critical thinking in the reading

• Thanks to Yifeng, Soroush, Zizhao, and Xiang for handling the course logistics.

If this course helps you kickstart your future endeavors in AI, please email us