TA Evaluations

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Please Also Complete Teaching Evaluations

will close on Sun, June 25th

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Decision Theory: Sequential Decisions

Computer Science cpsc322, Lecture 34

(Textbook Chpt 9.3)

June, 22, 2017

"Single" Action vs. Sequence of Actions

Set of primitive decisions that can be treated as a single macro decision to be made *before acting*

- Agent makes observations
- Decides on an action
- Carries out the action

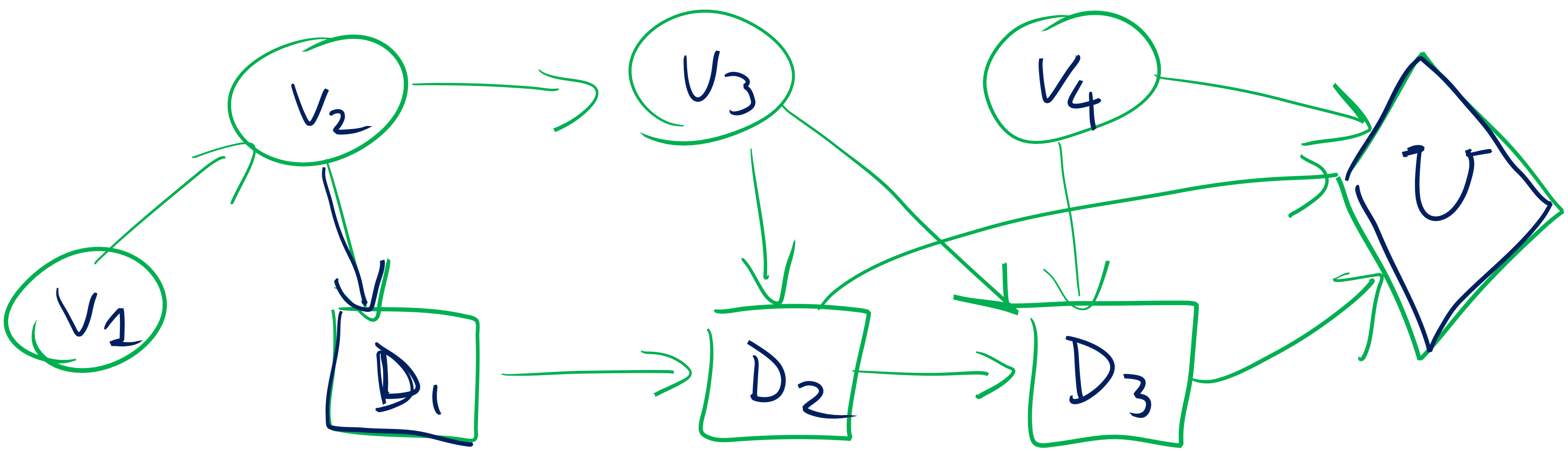
Lecture Overview

- Sequential Decisions
  - Representation
  - Policies
- Finding Optimal Policies

Sequential decision problems

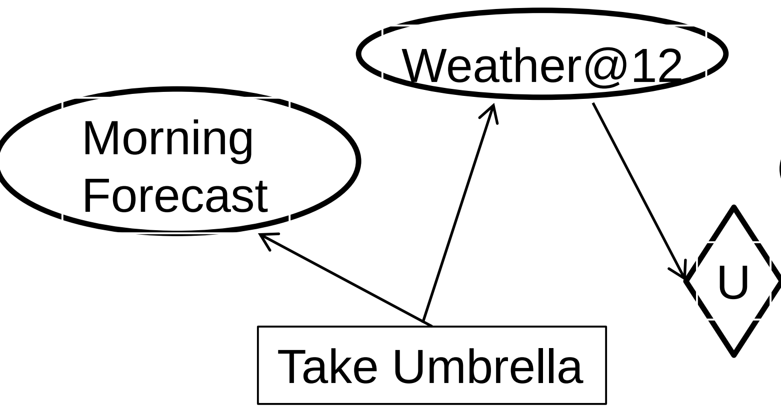
- A sequential decision problem consists of a sequence of decision variables D_1 ,･･･..,D_n.
- Each D_i has an information set of variables pD_i, whose value will be known at the time decision D_i is made.

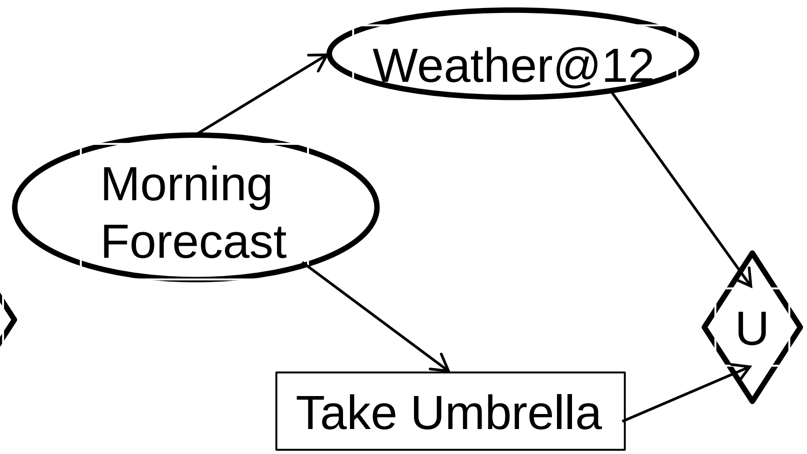
$pD_3 = \{D_2\ V_3\ V_4\}$



Sequential decisions : Simplest possible

- Only one decision! (but different from one-off decisions)
- Early in the morning. I listen to the **weather forecast**, shall I take my **umbrella** today? (I'll have to go for a long walk **at noon**)
- What is a reasonable decision network ?





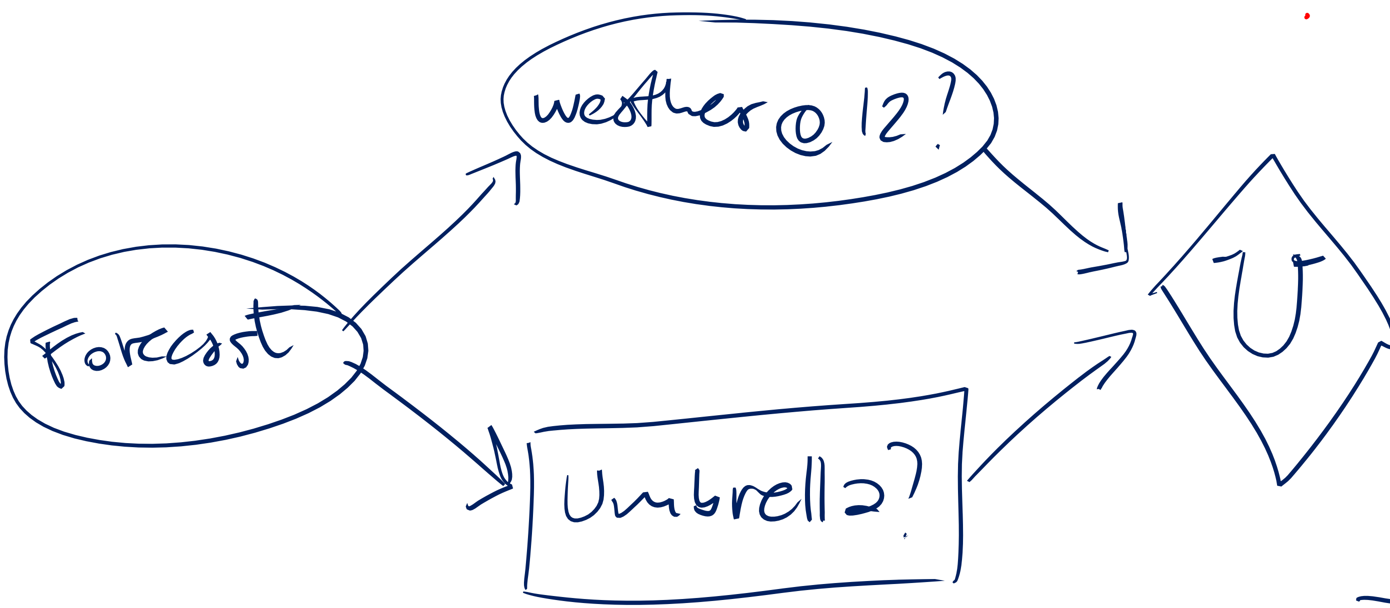
A.

B.

C . None of these

Sequential decisions : Simplest possible

- Only one decision! (but different from one-off decisions)
- Early in the morning. Shall I take my **umbrella** today? (I' ll have to go for a long walk at noon)
- Relevant Random Variables?



Policies for Sequential Decision Problem: Intro

- A **policy** specifies what an agent should do under each circumstance (for each decision, consider the parents of the decision node)

In the *Umbrella* "degenerate" case:

D_1 ? T F

One possible Policy

pD_1				
Rainy	→ R	T	F	T ...
Cloudy	→ C	T	F	T ...
Sunny	→ S	F	F	T ...

3 policies

How many policies? 2^3

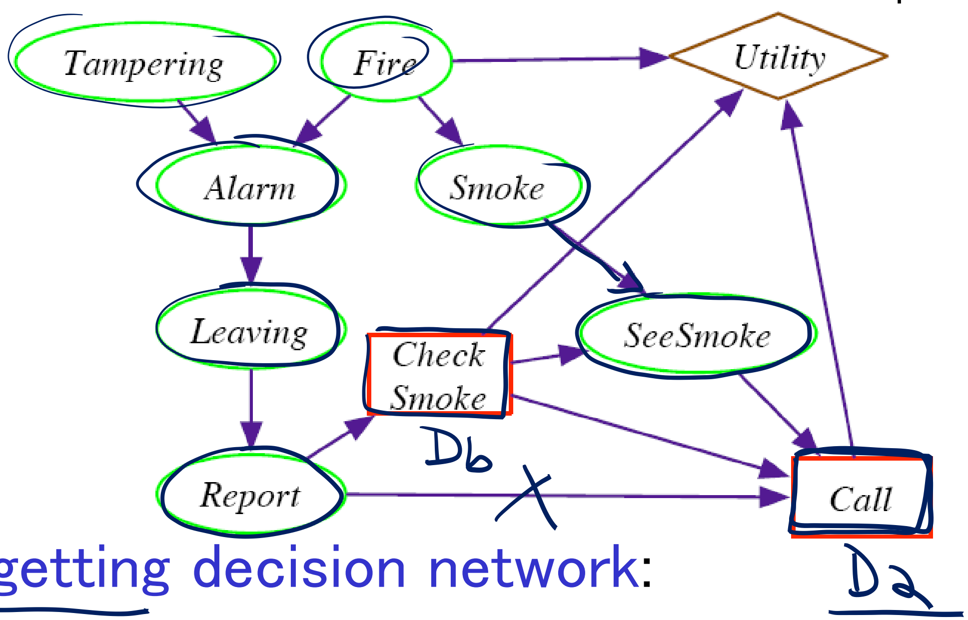
dom(pD)

dom(D)

dom = domain

Sequential decision problems: "complete" Example

- A sequential decision problem consists of a sequence of decision variables $D_1, \ldots, D_n$.
- Each D_i has an information set of variables pD_i, whose value will be known at the time decision D_i is made.



$pCS = \{R\}$

$pC = \{R, CS, SS\}$

No-forgetting decision network:

- decisions are totally ordered
- if a decision D_b comes before D_a, then
  - D_b is a parent of D_a
  - any parent of D_b is a parent of D_a

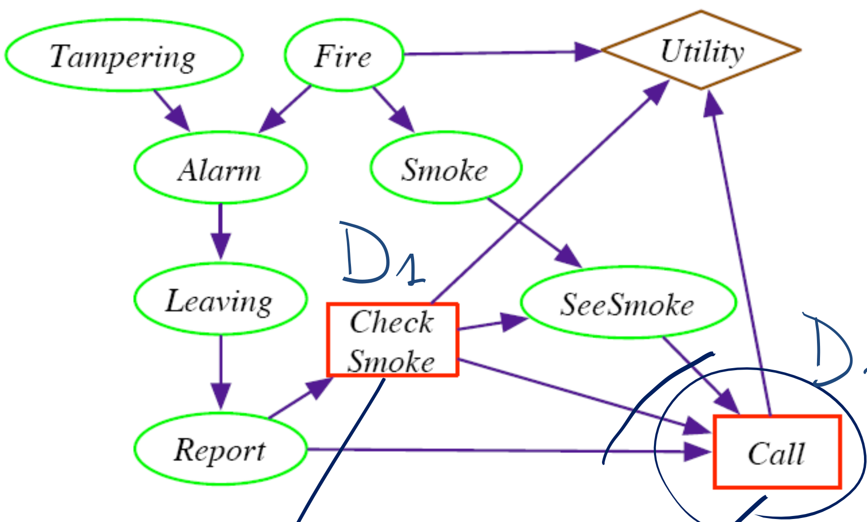
$pCS \subseteq pC$

Policies for Sequential Decision Problems

- A **policy** is a sequence of $\delta_1, \cdots, \delta_n$ **decision functions**

$$\delta_i : \underline{\mathrm{dom}(pD_i)} \rightarrow \underline{\mathrm{dom}(D_i)}$$

- This policy means that when the agent has observed $O \in \mathrm{dom}(pD_i)$, it will do $\delta_i(O)$



Example: δ_1

Report	Check Smoke
T	T T F F
F	T F T F

δ_2

Report	CheckSmoke	SeeSmoke	Call
true	true	true	true
true	true	false	false
true	false	true	true
true	false	false	false
false	true	true	true
false	true	false	false
false	false	true	false
false	false	false	false

8

How many policies?

$2^2 * 2^8$

Lecture Overview

- Recap
- Sequential Decisions
- Finding Optimal Policies

When does a possible world satisfy a policy?

- A possible world specifies a value for each random variable and each decision variable.
- **Possible world w satisfies policy δ**, written $w \models \delta$ if the value of each decision variable is the value selected by its decision function in the policy (when applied in w).

$w \not\models \delta$

w

VARs	
Fire	true
Tampering	false
Alarm	true
Leaving	true
Report	false
Smoke	true
SeeSmoke	true
CheckSmoke	true
Call	true

Rnd.

Dec.

δ

Decision function for…

Report	**Check Smoke**
true	true
false	false

$\not\models$

Decision function for…

Report	**CheckSmoke**	**SeeSmoke**	**Call**
true	true	true	true
true	true	false	false
true	false	true	true
true	false	false	false
false	true	true	true
false	true	false	false
false	false	true	false
false	false	false	false

When does a possible world satisfy a policy?

- Possible world w satisfies policy δ, written $w \models \delta$ if the value of each decision variable is the value selected by its decision function in the policy (when applied in w).

w_1

VARs	
Fire	true
Tampering	false
Alarm	true
Leaving	true
Report	true
Smoke	true
SeeSmoke	true
CheckSmoke	true
Call	true

δ

Decision function for…

Report	**Check Smoke**
true	true
false	false

$\checkmark$

Decision function for…

Report	**CheckSmoke**	**SeeSmoke**	**Call**
true	true	true	true
true	true	false	false
true	false	true	true
true	false	false	false
false	true	true	true
false	true	false	false
false	false	true	false
false	false	false	false

A. $w_1 \models \delta$

B. $w_1 \not\models \delta$

C . Cannot tell

iclicker.

Expected Value of a Policy

- Each possible world w has a probability $P(w)$ and a utility $U(w)$
- The expected utility of policy δ is

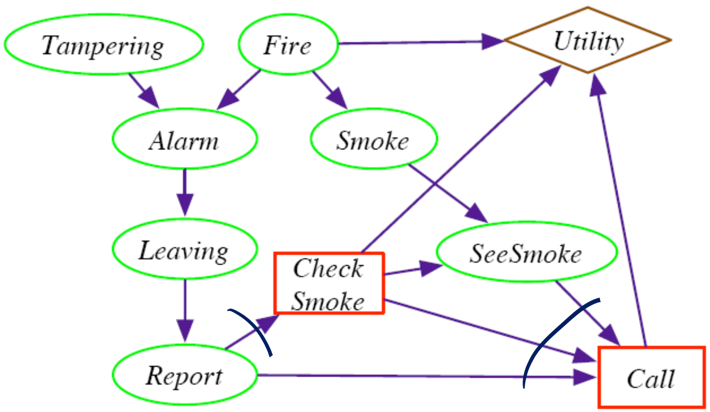
$$\sum_{w \models \delta} P(w) * U(w)$$

- The optimal policy is one with the max expected utility.

Lecture Overview

- Recap
- Sequential Decisions
- Finding Optimal Policies (Efficiently)

Complexity of finding the optimal policy: how many policies?



- How many assignments to parents?

  CS 2 C 2^3

- How many decision functions? (binary decisions)

  2^{2^2} 2^{2^3}

- How many policies?

  product $2^{2^2} * 2^{2^3}$

- If a decision *D* has *k* binary parents, how many assignments of values to the parents are there?

  2^K

- If there are *b* possible actions (possible values for D), how many different decision functions are there?

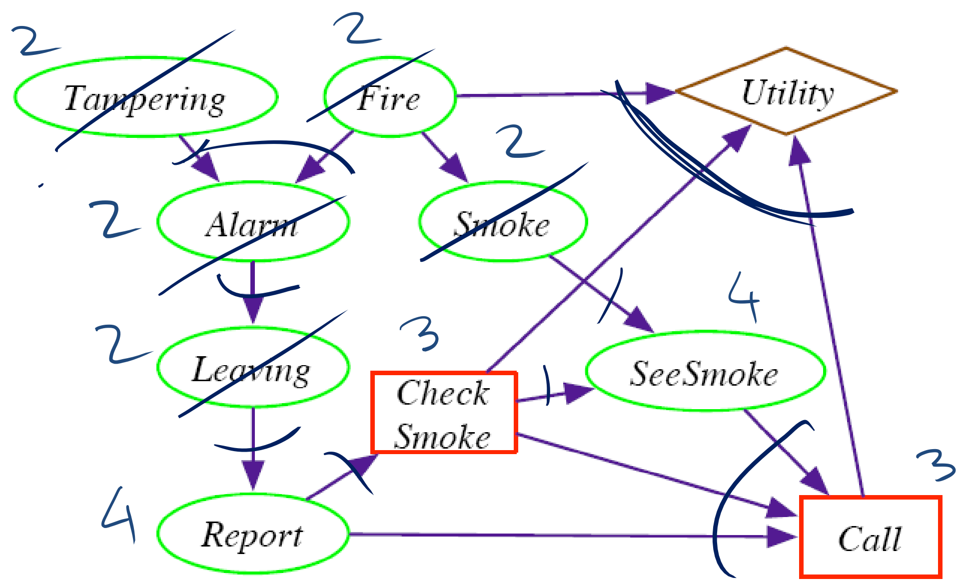
  $\boxed{b^{2^K}}$

- If there are *d* decisions, each with *k* binary parents and *b* possible actions, how many policies are there?

  $\left(b^{2^K}\right)^d$

Finding the optimal policy more efficiently: VE

1. Create a factor for each conditional probability table and a factor for the utility.
2. **Sum out** random variables that are not parents of a decision node.
3. **Eliminate** (aka sum out) the decision variables
4. **Sum out** the remaining random variables.
5. **Multiply the factors**: this is the expected utility of the optimal policy.



Eliminate the decision Variables: step3 details

- Select a variable D that corresponds to the latest decision to be made
  - this variable will appear in only one factor with its parents
- Eliminate D by maximizing. This returns:
  - A new factor to use in VE, $\max_D f$
  - The optimal decision function for D, $\arg\max_D f$
- Repeat till there are no more decision nodes.

Example: Eliminate CheckSmoke

Report	CheckSmoke	Value
true	true	−5.0
true	false	−5.6
false	true	−23.7
false	false	−17.5

Report	Value
true	−5.0
false	−17.5

New factor

Decision Function

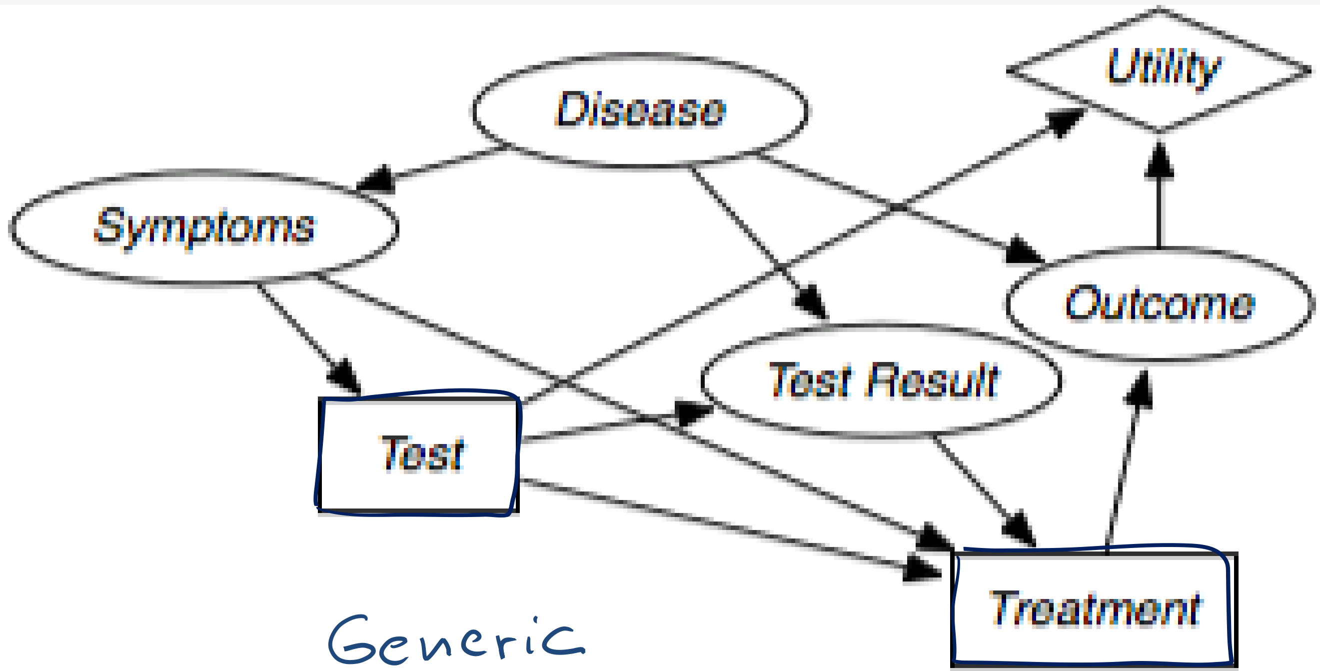
Report	CheckSmoke
true	true
false	false

VE elimination reduces complexity of finding the optimal policy

- We have seen that, if a decision *D* has *k* binary parents, there are *b* possible actions, If there are d decisions,
- Then there are: $\boxed{(b^{2^k})^d \text{ policies}}$
- Doing variable elimination lets us find the optimal policy after considering only $d \cdot b^{2^k}$ policies (we eliminate one decision at a time)
  - VE **is much more efficient** than searching through policy space.
  - However, this complexity is **still doubly-exponential** we'll only be able to handle relatively small problems.

+ give up nonforgetting assump
+ approx. algorithms

422



Generic

Figure 9.8: Decision network for diagnosis

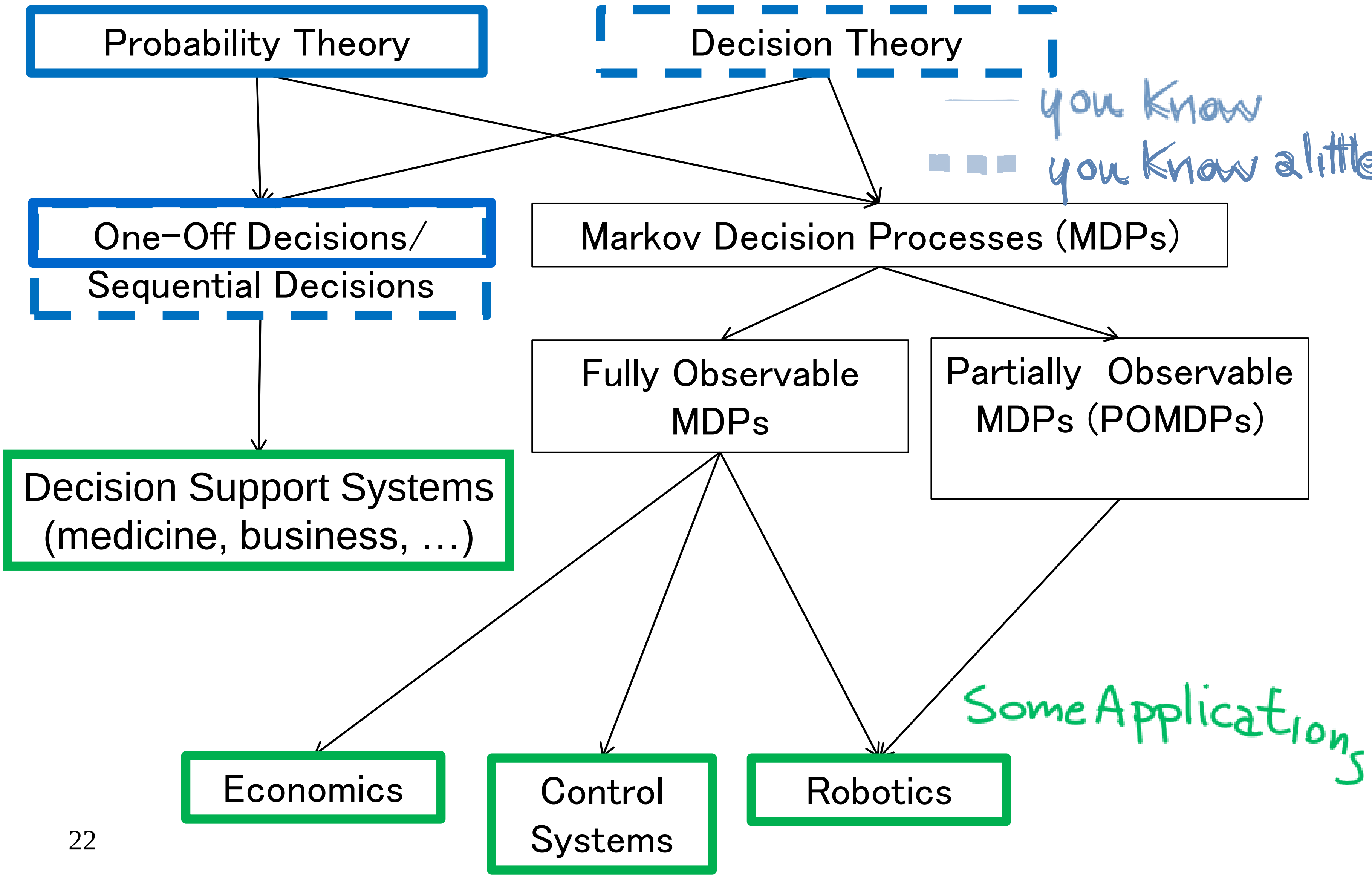
to select what test to apply
and then what treatment to prescribe

Learning Goals for today's class

You can:

- Represent **sequential decision problems** as decision networks. And explain the **non forgetting property**
- Verify whether a **possible world satisfies a policy** and define the **expected value of a policy**
- Compute the **number of policies** for a decision problem
- **Compute the optimal policy** by Variable Elimination

Big Picture: Planning under Uncertainty



Cpsc 322 Big Picture

Environment

Problem		Deterministic	Stochastic
Static	Constraint Satisfaction	Arc Consistency *Vars + Constraints* Search → for CSP SLS	
	Query	*Logics* → CSP Search → for Inference	*Belief Nets* Var. Elimination *Markov Chains*
Sequential	Planning	*STRIPS* → CSP Search → for complex planning	*Decision Nets* Var. Elimination

Representation

Reasoning Technique

422 big picture

StarAI (statistical relational AI)

Hybrid: Det +Sto

Prob CFG

Prob Relational Models

Markov Logics

	Deterministic	Stochastic
Query	*Logics* *First Order Logics* *Ontologies* • Full Resolution • SAT	*Belief Nets* Approx. : Gibbs *Markov Chains and HMMs* Forward, Viterbi…. Approx. : Particle Filtering *Undirected Graphical Models* *Markov Networks* *Conditional Random Fields*
Planning		*Markov Decision Processes and Partially Observable MDP* • Value Iteration • Approx. Inference *Reinforcement Learning*

Applications of AI

Representation

Reasoning Technique

More AI ..

StarAI (statistical relational AI)

Hybrid: Det +Sto

Prob CFG
Prob Relational Models
Markov Logics

Machine Learning

Knowledge Acquisition

Preference Elicitation

	Deterministic	Stochastic
Query	*Logics* *First Order Logics* *Ontologies*	*Belief Nets* *Markov Chains and HMMs* *Undirected Graphical Models* *Markov Networks* *Conditional Random Fields*
Planning		*Markov Decision Processes and Partially Observable MDP* *Reinforcement Learning*

Where are the components of our representations coming from?

The probabilities?

The utilities?

The logical formulas?

From people and from data!

Some of our Grad Courses

522: Artificial Intelligence II : Reasoning and Acting Under Uncertainty

Sample Advanced Topics…..

Relational Reinforcement Learning for Agents in Worlds with Objects, relational learning.

– Probabilistic Relational Learning and Inductive Logic Programming at a Global Scale,

Some of our Grad Courses

503: Computational Linguistics I / Natural Language Processing

Sample Advanced Topics…..

- Topic Modeling (LDA) – Large Scale Graphical Models
- Discourse Parsing by Deep Learning (Neural Nets)
- Abstractive Summarization

Other AI Grad Courses: check them out

532: Topics in Artificial Intelligence (different courses)

- User-Adaptive Systems and Intelligent Learning Environments
- Foundations of Multiagent Systems

540: Machine Learning

505: Image Understanding I: Image Analysis
525: Image Understanding II: Scene Analysis

515: Computational Robotics

Announcements

Assignment 4. Due Sunday, June 25th @ 11:59 pm. Late submissions will not be accepted, and late days may not be used..

FINAL EXAM: Thu, Jun 29 at 7-9:30 PM Room: BUCH A101

Final will comprise: 10 –15 short questions + 3–4 problems

- Work on all **practice exercises (including 9.B)** and **sample review questions and problems (will be posted over the weekend)**
- While you revise the **learning goals**, work on **review questions** – I may even reuse some verbatim ☺
- **Come to remaining Office hours! (schedule for next week will be posted on piazza) My office hour tomorrow will be at 2PM**