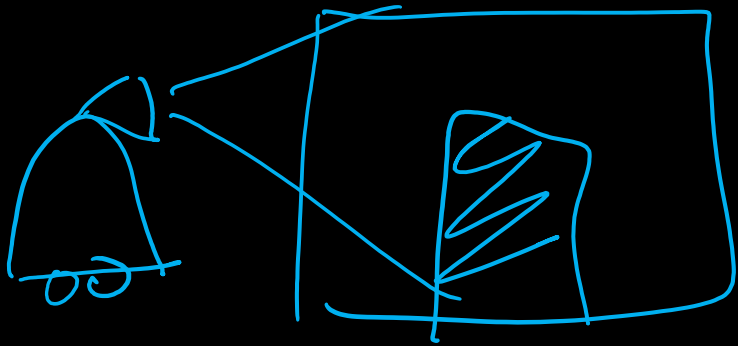


Decision Making I

Katie DC

Notes from Decision Making Under Uncertainty, by M.J. Kochenderfer

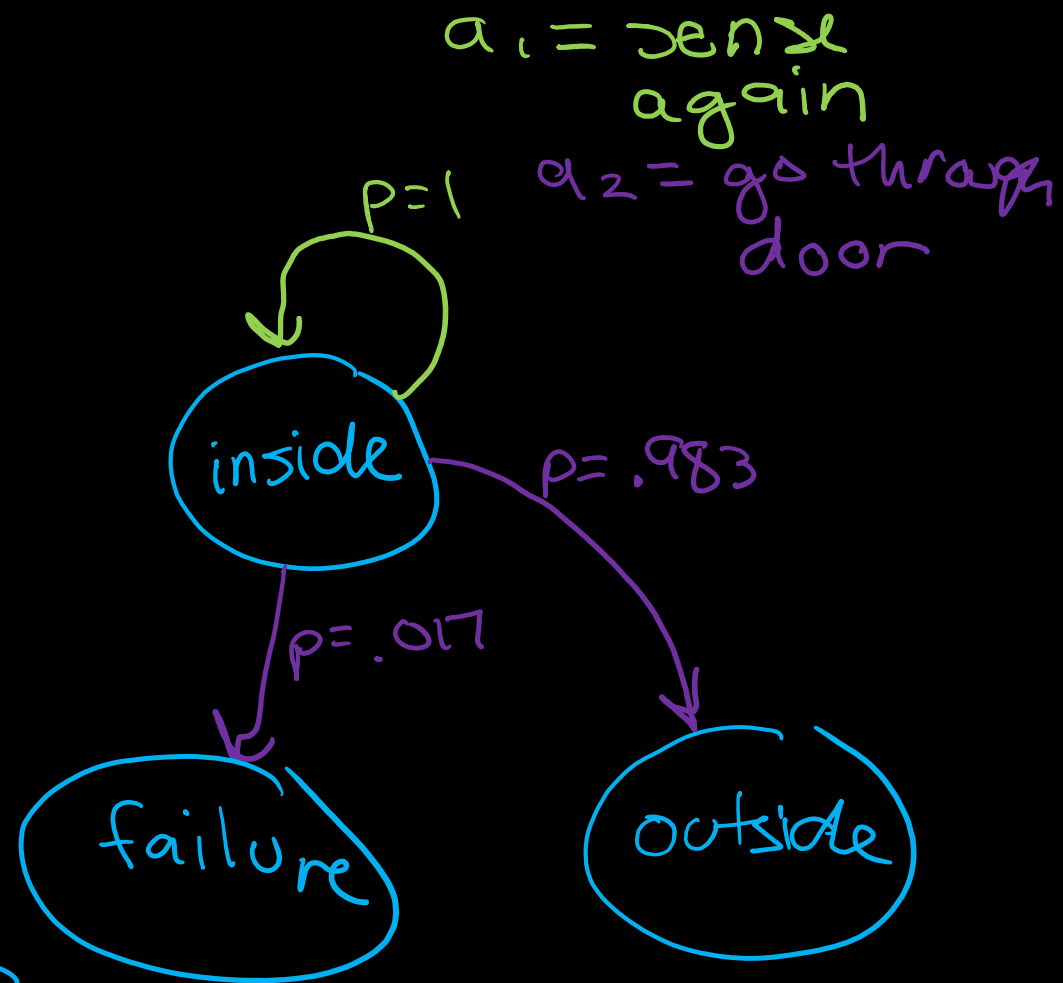
Recall Estimation Example



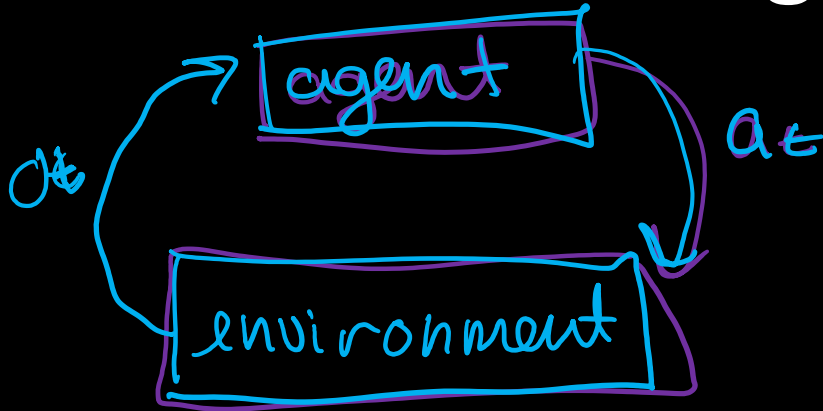
using Bayes Filtering, we can recursively update our belief about the state of the door

$$\text{bel}(x_{t=2} = \text{is open}) = .983$$

- should we take an action?
- should we probe or explore?



Decision Making Systems



Methods

1. Explicit programming
2. Supervised learning
3. Optimization / optimal control
4. Planning
 - Given a stochastic model, how to algorithmically de
5. Reinforcement Learning
 - If model is unknown (or very complex), learn policy through experience



↑ 16k ↓ 485 Share

BEST

u/Skizm · 2mo

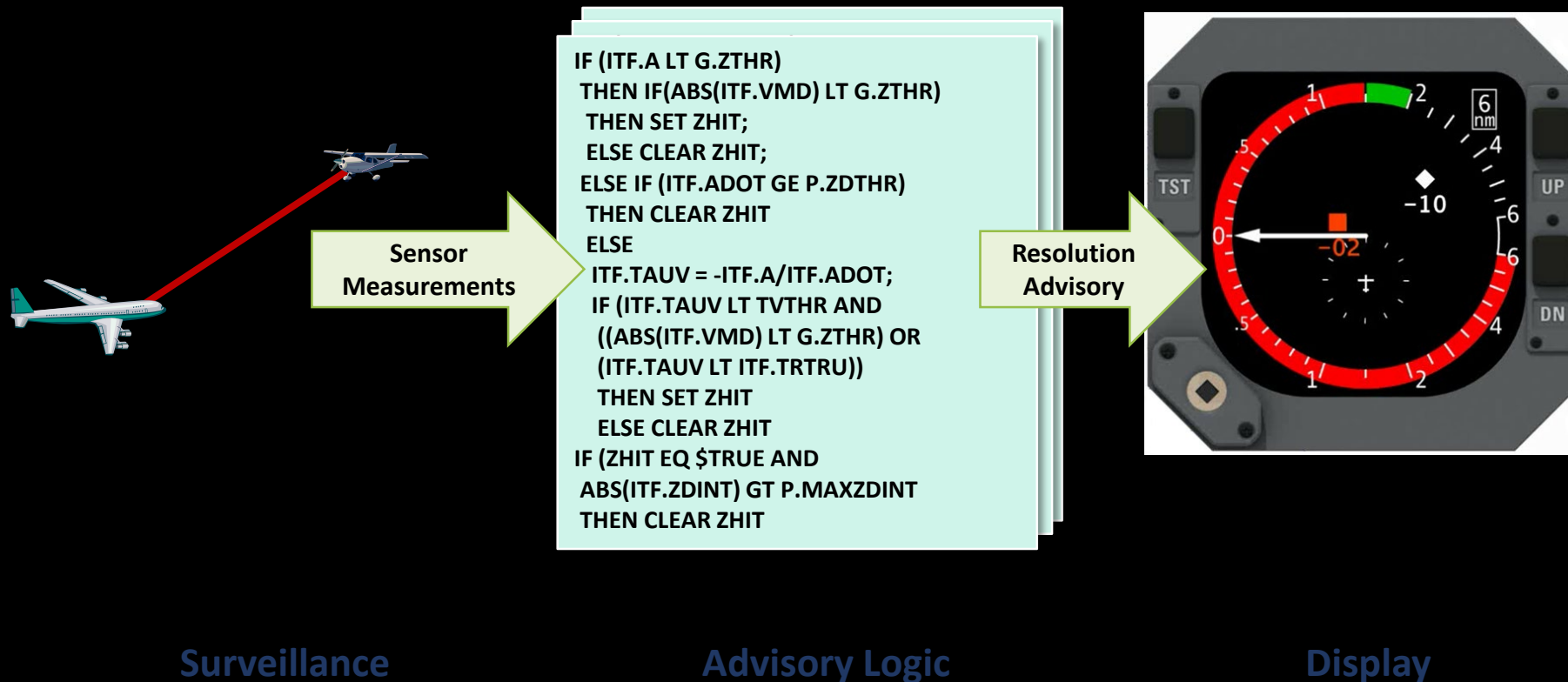
```
if (goingToCrashIntoEachOther)  
{ dont(); }
```



as a robotics major i can confirm this is 100%
how coding works

burden on designer
doesn't generalize well
more later
require a (continuous) good model

Traffic Alert and Collision Avoidance System (TCAS)



PROCESS Reversal_modeling;

```

. Default modeled separation for current RA is 0 if current RA is negative;
. Set own altitude and own rate to own tracked altitude and own tracked rate;

. IF (own does not follow his RAs)
.   THEN Model separation achieved assuming RA not followed;
.   . IF (current RA is a climb RA)
.   .   THEN CLEAR flag indicating the sense of the RA after a reversal;
.   .   ELSE SET flag indicating the sense of the RA after a reversal;
.   . IF (modeled separation achieved by continuing current RA greater than 1.2 *
.   .   P.CROSSTHR)
.   .   THEN CLEAR reversal flag in ITF
.   . ELSE
.   .   <Begin own is assumed to follow its RA>
.   .   IF (current RA is positive)
.   .   . THEN model response to current RA;
.   .   .   <model maximum displayable rate for climb if current rate exceeds
.   .   .   maximum displayable rate or minimum displayable rate for descent if
.   .   .   current rate is less than minimum displayable rate>
.   .   . IF (tracked response lags modeled response in RA direction AND
.   .   .   time since RA less than a parameter time AND
.   .   .   own's rate has not changed by more than P.MODEL_ZD since the
.   .   .   RA was first issued)
.   .   .   THEN set own altitude and own rate to modeled altitude and rate
.   .   .   for use in reversal modeling;
.   .   . Model separation achieved by continuing current RA;
.   .   . Set delay time to greater of pilot delay time remaining for last advisory against a
.   .   .   new threat, and the pilot quick reaction time;
.   .   . IF (considering a reversal from a descend RA to a climb RA)
.   .   .   THEN set own goal rate to greater of own tracked rate (or maximum
.   .   .   displayable rate, whichever is less) and nominal climb rate;
.   .   .   ELSE IF (own too close to ground to descend)
.   .   .   . THEN set own goal rate to zero;
.   .   .   . ELSE set own goal rate to lesser of own tracked rate (or minimum
.   .   .   . displayable rate, whichever is greater) and nominal descent
.   .   .   . rate;
.   .   . IF (vertical chase, low VMD geometry was not the reason for considering
.   .   .   reversal)
.   .   .   THEN IF (intruder causing crossing OR (intruder level AND own crossing
.   .   .   . from above) OR intruder rate and own modeled rate are opposite in sign)
.   .   .   .   THEN use outer rate bound to model intruder;
.   .   .   .   ELSE use inner rate bound to model intruder;
.   .   .   . ELSE use intruder's tracked vertical rate to model intruder;
.   .   .   CALL MODEL_SEP
.   .   .   IN (delay, goal rate, own altitude, own rate, acceleration response, sense after
.   .   .   . reversal, intruder altitude, modeled intruder rate, ITF entry)
.   .   .   OUT (predicted separation for sense reversal);
.   .   . IF (Predicted separation for sense reversal is not positive OR
.   .   .   modeled separation achieved by continuing current RA GE G.ALIM)
.   .   .   THEN CLEAR reversal flag in ITF;
.   .   . <End own is assumed to follow its RA>

```

END Reversal_modeling;

RESOLUTION HIGH-LEVEL LOGIC

6-P22

PROCESS Reversal_modeling;

```

. NOMINAL_SEP = 0;
. Z = G.ZOWN;
. ZD = G.ZDOWN;
. DELAY = 0;

. IF (G.OWN_FOLLOW EQ FALSE)
.   THEN CALL MODEL_SEP
.   . IN (DELAY, ZD, Z, ZD, P.VACCEL, OWNTENT(7), ITF.ZINT, ITF.ZDINT, ITF.entry)
.   . OUT (NOMINAL_SEP);
.   . IF (OWNTENT(7) EQ $TRUE)
.   .   THEN NEW_SENSE = $FALSE;
.   .   ELSE NEW_SENSE = $TRUE;
.   . IF (NOMINAL_SEP GT 1.2 * P.CROSSTHR)
.   .   THEN CLEAR ITF.REVERSE;
.   . ELSE
.   .   <Begin own is assumed to follow its RA>
.   .   IF (OWNTENT(5,6) EQ '00')
.   .   . THEN DELAY = MAX(P.TV1 - (G.TCUR - G.TPOSRA), 0);
.   .   . IF (OWNTENT(7) EQ $FALSE)
.   .   .   THEN ZDGOAL = MAX(MIN(G.ZDOWN, P.MAXDRATE), P.CLMRT);
.   .   .   ELSE ZDGOAL = MIN(MAX(G.ZDOWN, P.MINDRATE), P.DESRT);
.   .   . CALL PROJECT_VERTICAL_GIVEN_ZDGOAL
.   .   .   IN ((G.TCUR - G.TPOSRA), G.ZTV, G.ZDTV, ZDGOAL, P.TV1, P.VACCEL)
.   .   .   OUT (ZPROJ, ZDPROJ);
.   .   . IF (((OWNTENT(7) EQ $FALSE AND ZPROJ GT G.ZOWN AND
.   .   .   (G.ZDOWN GE G.ZDTV - P.MODEL_ZD)) OR
.   .   .   (OWNTENT(7) EQ $TRUE AND ZPROJ LT G.ZOWN AND
.   .   .   (G.ZDOWN LE G.ZDTV + P.MODEL_ZD))) AND
.   .   .   G.TCUR - G.TPOSRA LT P.MODEL_T)
.   .   .   THEN Z = ZPROJ;
.   .   .   ZD = ZDPROJ;
.   .   . CALL MODEL_SEP
.   .   .   IN (DELAY, ZDGOAL, Z, ZD, P.VACCEL, OWNTENT(7),
.   .   .   . ITF.ZINT, ITF.ZDINT, ITF.entry)
.   .   .   OUT (NOMINAL_SEP);
.   .   . IF (OWNTENT(7) EQ $TRUE)
.   .   .   THEN NEW_SENSE = $FALSE;
.   .   .   ELSE NEW_SENSE = $TRUE;
.   .   . DELAY = MAX(P.TV1 - (G.TCUR - G.TLASTNEWRA), P.QUICKREAC);
.   .   . IF (NEW_SENSE EQ $FALSE)
.   .   .   THEN ZDGOAL = MAX(P.CLMRT, MIN(G.ZDOWN, P.MAXDRATE));
.   .   .   ELSE IF (G.NODESCENT EQ $TRUE)
.   .   .   . THEN ZDGOAL = 0;
.   .   .   . ELSE ZDGOAL = MIN(P.DESRT, MAX(G.ZDOWN, P.MINDRATE));
.   .   . IF (G.REV_CONSDRD EQ FALSE)
.   .   .   THEN IF ((ITF.INT_CROSS EQ $TRUE) OR (ITF.ZDINT EQ 0 AND
.   .   .   . ITF.RZ GT 0) OR (ITF.ZDINT * G.ZDMODEL LT 0))
.   .   .   . THEN MZDINT = ITF.ZDOUTR;
.   .   .   . ELSE MZDINT = ITF.ZDINR;
.   .   .   . ELSE MZDINT = ITF.ZDINT;
.   .   . CALL MODEL_SEP
.   .   .   IN (DELAY, ZDGOAL, Z, ZD, P.RACCEL, NEW_SENSE, ITF.ZINT, MZDINT, ITF.entry)
.   .   .   OUT (ZMP);
.   .   . IF (ZMP LE 0 OR NOMINAL_SEP GE G.ALIM)
.   .   .   THEN CLEAR ITF.REVERSE;
.   .   . <End own is assumed to follow its RA>

```

END Reversal_modeling;

RESOLUTION LOW-LEVEL LOGIC

6-P23

Why is it hard?

State Uncertainty



Dynamic Uncertainty



Multiple Objectives

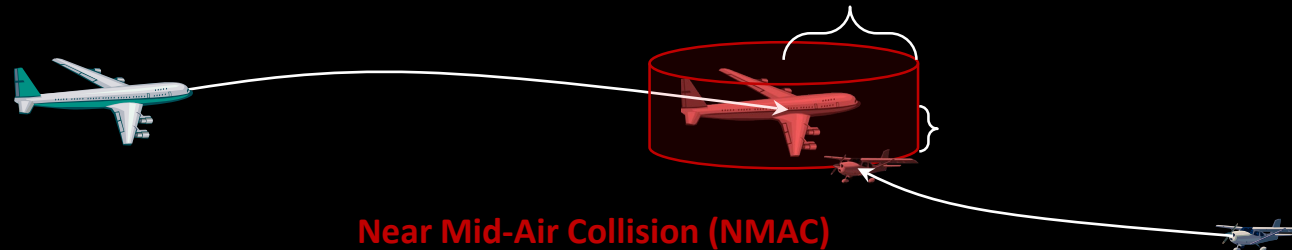


Simplified MDP



State space	Action space
<ul style="list-style-type: none">• Relative altitude• Own vertical rate• Intruder vertical rate• Time to lateral NMAC• State of advisory	<ul style="list-style-type: none">• Clear of conflict• Climb > 1500 ft/min• Climb > 2500 ft/min• Descend > 1500 ft/min• Descend > 2500 ft/min
Dynamic model	Reward model
<ul style="list-style-type: none">• Head-on, constant closure• Random vertical acceleration• Pilot response delay (5 s)• Pilot response strength (1/4 g)• State of advisory	<ul style="list-style-type: none">• NMAC (-1)• Alert (-0.01)• Reversal (-0.01)• Strengthen (-0.009)• Clear of conflict (0.0001)

Simplified MDP

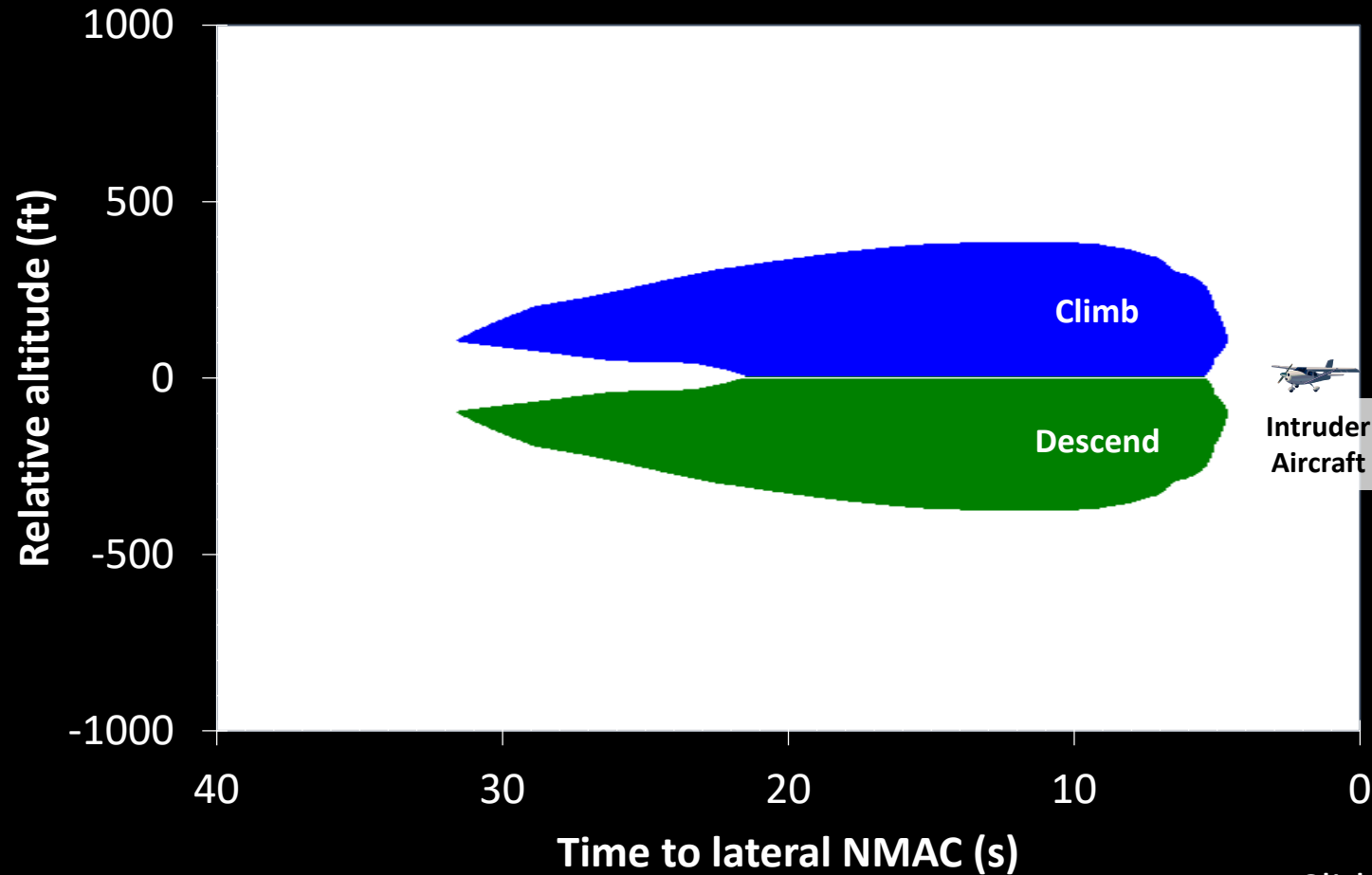


State space	Action space
<ul style="list-style-type: none">• Relative altitude• Own vertical rate• Intruder vertical rate• Time to lateral NMAC• State of advisory	<ul style="list-style-type: none">• Clear of conflict• Climb > 1500 ft/min• Climb > 2500 ft/min• Descend > 1500 ft/min• Descend > 2500 ft/min
Dynamic model	Reward model
<ul style="list-style-type: none">• Head-on, constant closure• Random vertical acceleration• Pilot response delay (5 s)• Pilot response strength (1/4 g)• State of advisory	<ul style="list-style-type: none">• NMAC (-1)• Alert (-0.01)• Reversal (-0.01)• Strengthen (-0.009)• Clear of conflict (0.0001)

Optimized Logic

Both Own and Intruder Level

Metric	TCAS	ACAS X
NMACs	169	3
Alerts	994,317	690,406
Strengthens	40,470	92,946
Reversals	197,315	9,569



Probabilities

1) conditional probability

$$P(A|B) = P(A, B) / P(B)$$

2) total probability

$$P(A) = \sum_{B \in \beta} P(A|B)P(B)$$

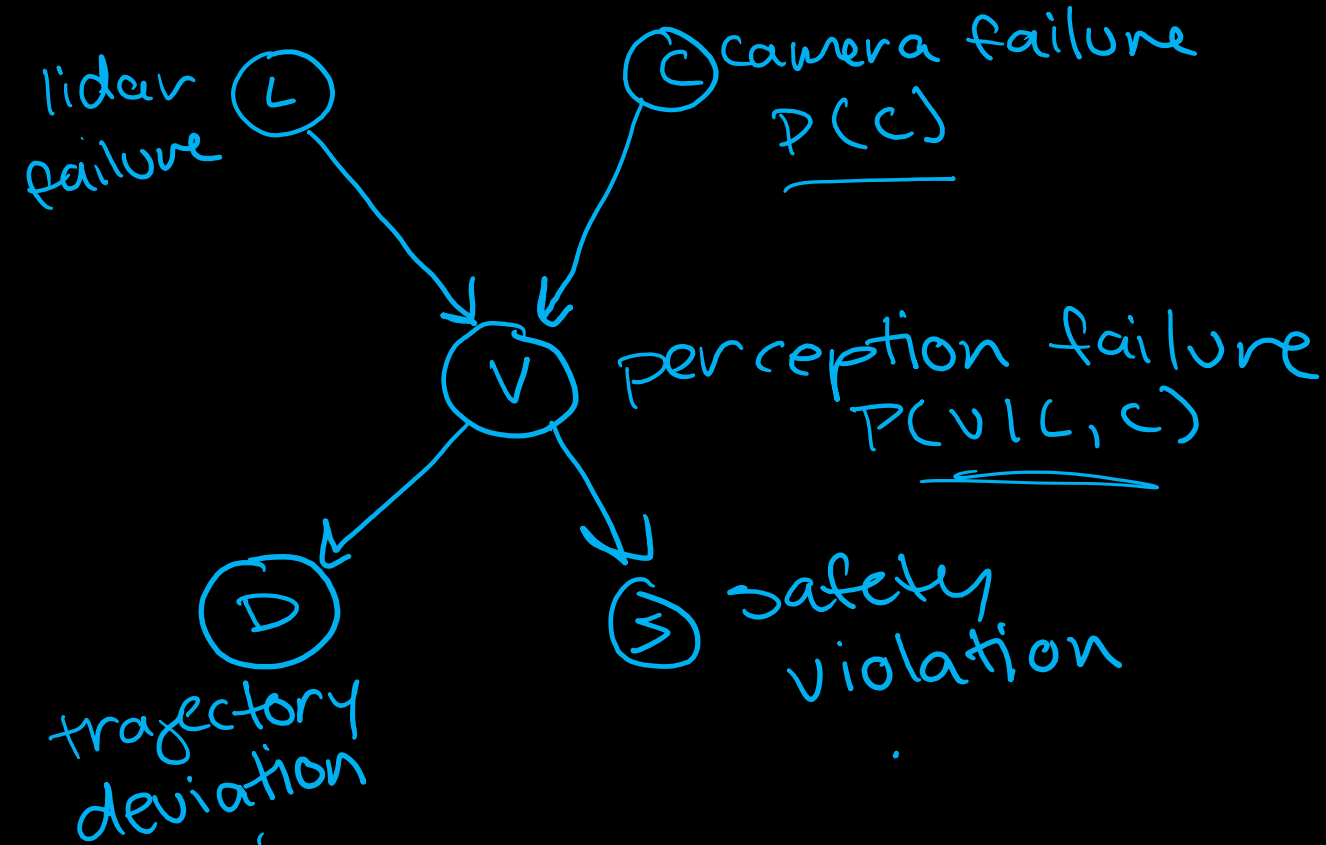
3) Bayes Rule

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

A	B	C	P(A,B,C)
0	0	0	0.08
0	0	1	0.15
0	1	0	0.05
0	1	1	0.10
1	0	0	0.14
1	0	1	0.18
1	1	0	0.19
1	1	1	0.11

Bayesian Networks (1)

compact representations of a joint probability distribution



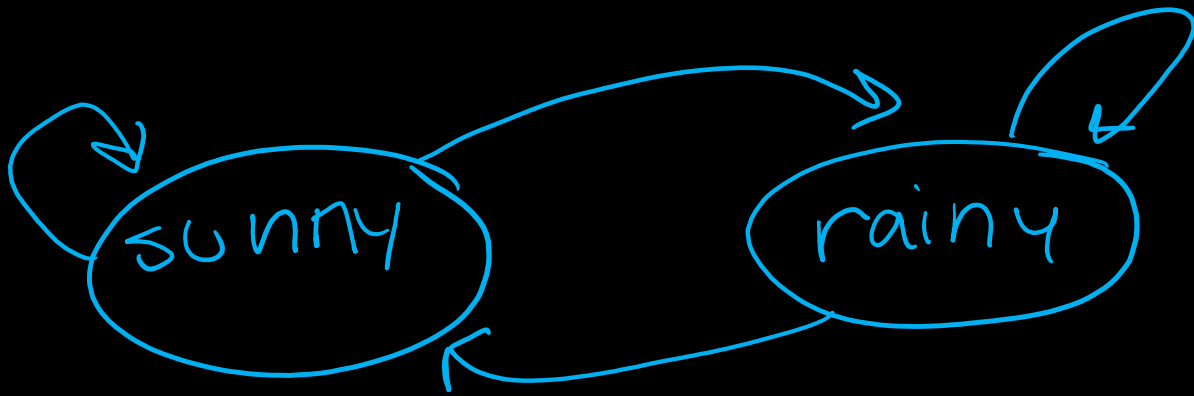
every node has a dist:
 $P(X_i | pa_{X_i})$

Continuous / Mixed Bayes Nets

Temporal Models: Markov Chains



x_t is the state of our system at time t
↳ pos + vel



	S	R
S	.9	.1
R	.2	.8

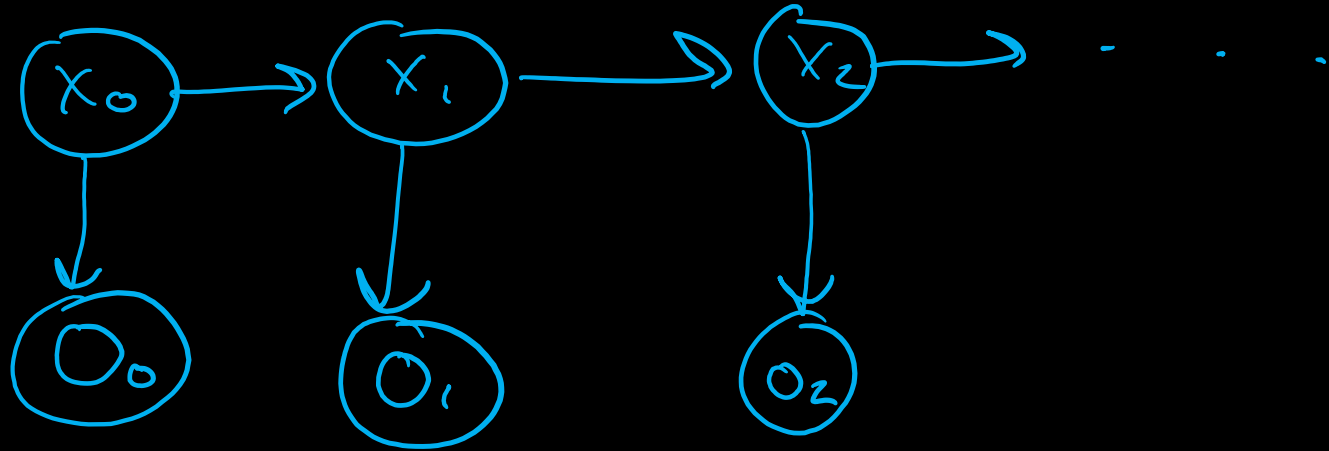
Markov Assumptions and Common Violations

Markov Assumption postulates that past and future data are independent if you know the current state.

What are some common violations?

- Unmodeled dynamics in the environment not included in state
 - E.g., moving people and their effects on sensor measurements in localization
- Inaccuracies in the probabilistic model
 - E.g., error in the map of a localizing agent or incorrect model dynamics
- Approximation errors when using approximate representations
 - E.g., discretization errors from grids, Gaussian assumptions
- Variables in control scheme that influence multiple controls
 - E.g., the goal or target location will influence an entire sequence of control commands

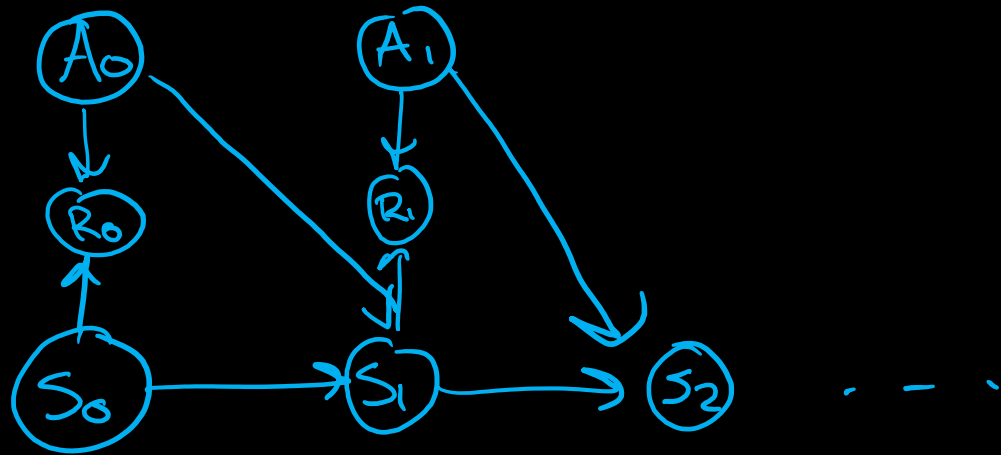
Hidden Markov Models



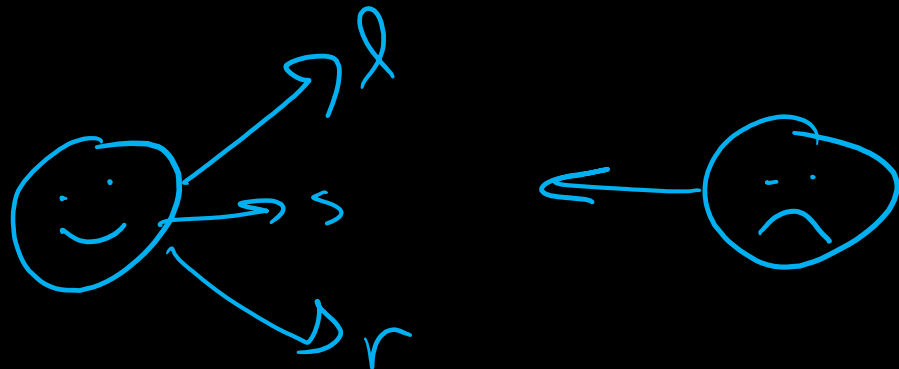
inference tools:

- filtering $P(X_k | O_{0:k})$
- prediction $P(X_k | O_{0:t}), k \geq t$
- smoothing $P(X_k | O_{0:t}), k < t$

Sequential Decision Making (1)



Markov Decision Process (S, A, T, R, γ)
 $T(s'|s, a) + \underline{R(s, a)}$



Utility and Reward

MDP rewards are generally additive components in a Utility function:

for some finite horizon w/ n decisions the utility associated w/ the sequence of rewards is

$$\sum_{t=0}^{n-1} r_t$$

Policies and Utility

- policy π specifies what action to executed from every state

$$a_t \leftarrow \pi(s_t) \text{ or } \pi(o_t)$$

- Expected utility ~~of~~ from executing π when starting at state s is denoted $U^\pi(s)$
- optimal policy π^* maximized expected utility

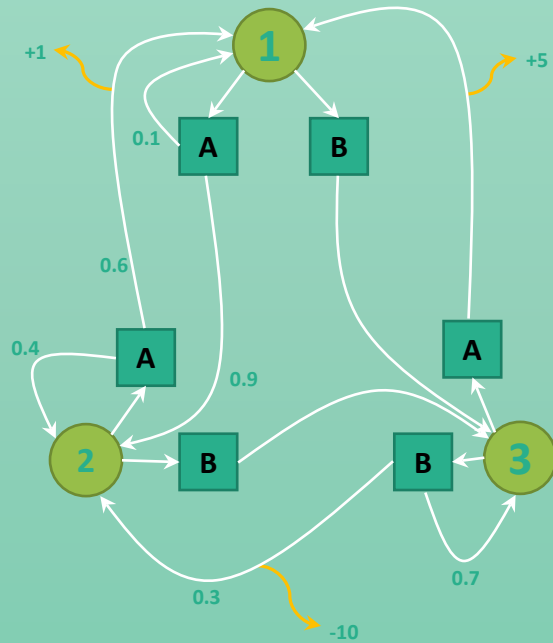
$$\pi^*(s) = \arg \max_{\pi} U^\pi(s)$$

Models of Optimal Behavior

- In the finite-horizon model, the agent should optimize expected reward for the next H steps: $E[\sum_{t=0}^H r_t]$
 - Continuously executing H -step optimal actions is known as receding horizon control
- In the infinite-horizon discounted model, agent should optimize: $E[\sum_{t=0}^H \gamma^t r_t]$
 - Discount factor is between 0 and 1, can be thought of as interest rate (reward now is worth more than reward later)
 - Keeps the utility of an infinite sequence finite

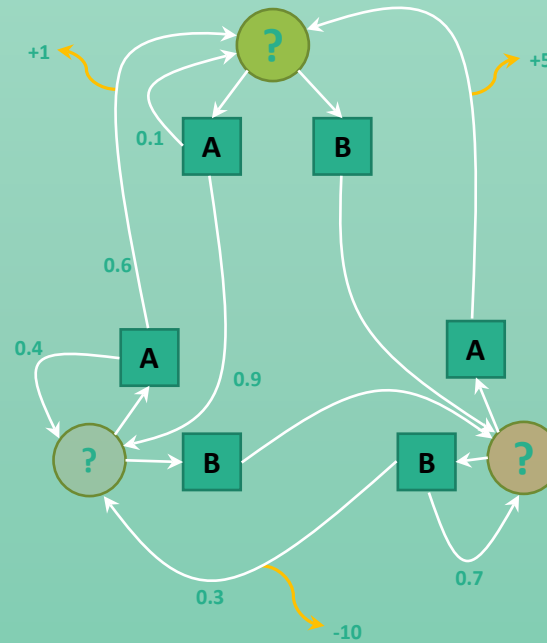
Markov Models

Markov Decision Processes (MDP)



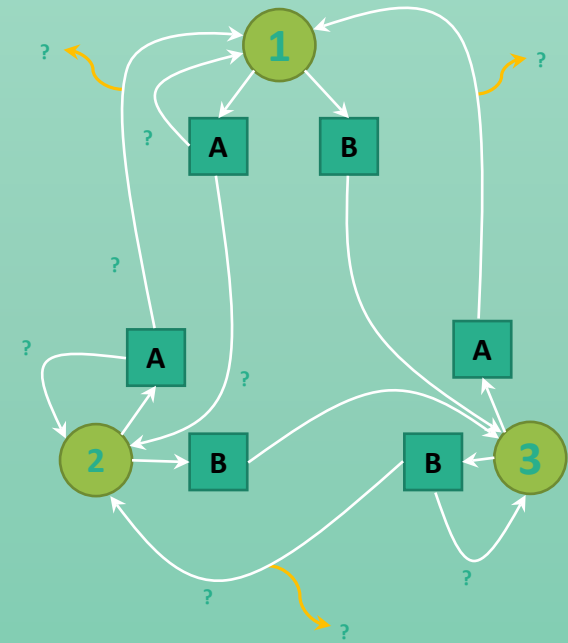
Uncertainty in effects of actions

Partially Observable MDP



Uncertainty in current state

Reinforcement Learning



Uncertainty in model