CS6462

Probabilistic and Explainable AI

Lesson 7

Model-Based Reasoning

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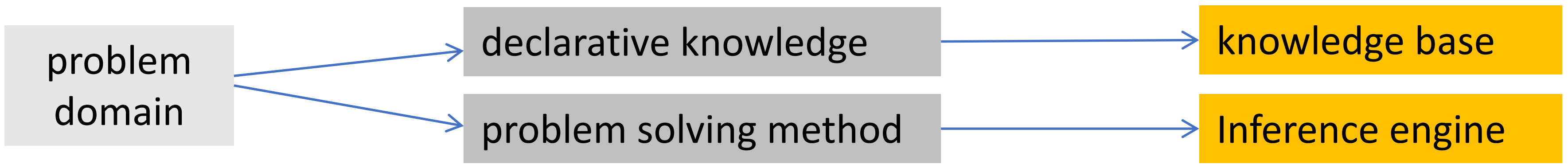
February 7, 2022

Models in AI

Definition (recall):

- a construct designed to respond in the same way as the system we would like to understand
- numerical models emulate stochasticity, i.e. using pseudorandom number generators, to simulate actually random phenomena and other uncertainties
- models produce *observations* we can measure in the real world
- <u>formal models are a precise statement of components to be used and the relationships among them</u>



Models in AI (cont.)

Model denotation:

- formal models - typically denoted mathematically

Example: a beta-Bernoulli model

formal functions

- statistical model, for generating a coin flip from a potentially biased coin

  $\boldsymbol{x \approx Beta(\alpha, \beta)}$, $\boldsymbol{x}$ is a latent variable (the bias of the coin)

  $\boldsymbol{y \approx Bernoulli(x)}$, $\boldsymbol{y}$ is the value of the flipped coin

Targets and Methods:

- capture instantaneous behavior, temporal behavior, structure
- methods: diagnosis, decision making, prediction, planning

Model-Based Reasoning

Definition:

- refers to inference methods used in expert systems based on a model of the physical world
- models used as a basis for fault detection and diagnosis - often referred to as *model based reasoning*

Advantages:

- models can be used for prediction of the impacts of faults as well as diagnosis
- application development is formalized - easier to check and reuse
- assumptions and limitations are likely to be cleared
- models are likely to reflect science rather than observed coincidences

Variations:

- normal operations or abnormal operations
- static vs. dynamic
- causal or non-causal
- compiled vs. first principles
- probabilistic vs. deterministic

quantitative - based on numbers and equations
and/or
qualitative - based on cause/effect

Models of Abnormal vs. Normal Operation

Application domain:

- systems characterized by numerical variables

Models of normal operation:

- algebraic equations, differential equations, neural nets, state transition diagrams

Fault detection:

- involves checking that the models are being followed in the observed sensor data

Models of abnormal operation:

- engineering models of normal behavior - complex and costly to develop and maintain
- alternative - develop models of abnormal behavior
- ultimately link root cause problems to observable symptoms

Static vs. Dynamic Models

Definition:

- dynamic models explicitly model behavior over time, while static models do not
- dynamic – traditionally quantitative models
- static – both quantitative and qualitative models
- static models provide a 'snapshot' of a system's response to a set of input conditions

Dynamic model example:

- state transition diagrams or Petri nets - model changes in state that occur over time

Static model example:

- a set algebraic equations

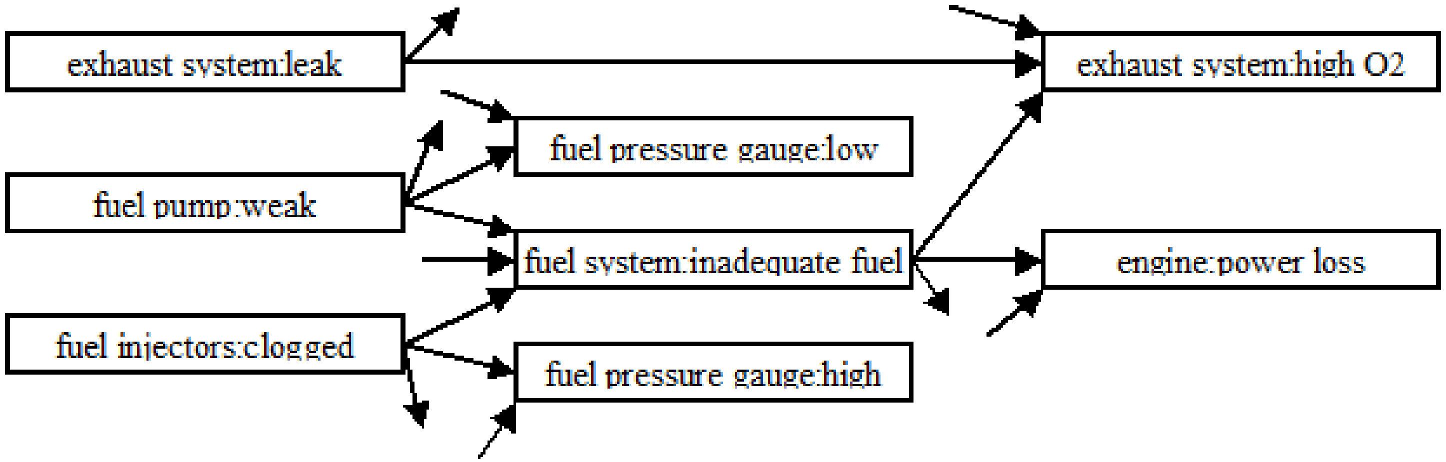
Causal Models

Definition:

- a qualitative model form using binary variables, usually represented as a set of variables as nodes in a directed graph

Example:

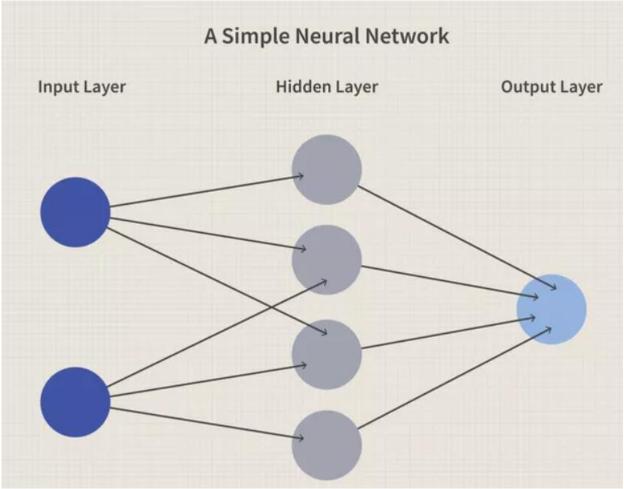
- a part of a cause/effect model of problems for vehicles
- boxes represent problems; links represent cause and effect



Compiled vs. First Principles Models

First Principles models:

- based on science laws or device implementation knowledge, rather than on data
- engineering design models, qualitative models such as causal fault propagation models, or state transition diagrams
- often referred to as using "*deep knowledge*"



Compiled models:

- simplified versions of more complex models
- empirical models - derived directly from data
  - use data derived from tests or from the output of simulation models
  - examples: regression models, neural nets
  - disadvantage: need to be rebuilt when there are changes in the data model

Probabilistic vs. Deterministic Models

Uncertainty:

lack of exact knowledge, regardless of what is the cause of this deficiency

Deterministic models:

- assume certainty in all aspects
- examples: timetables, pricing structures, a linear programming model, maps, etc.

Probabilistic (Stochastic) models:

- represent uncertainty
- examples: queueing models, markov chains, most simulations, etc.

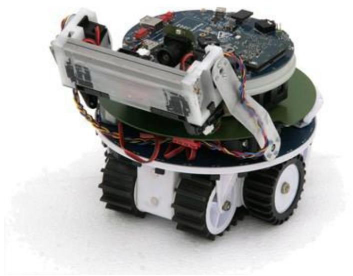
Uncertainty – Classification

Stems from various sources (classification by Regan at al.):

- ***inherent randomness*** – uncertainty about the outcome; can be quantified
- ***measurement error*** – causes uncertainty about the value of the measured quantity; can be estimated by statistical methods, if several samples are taken
- ***systematic error*** – error in the measurements resulting from a bias in the sampling; difficult to quantify
- ***natural variation*** – real systems change in time and place, and so do the parameters
- ***model uncertainty*** – models are abstractions of the real systems; less important variables and interactions can be left out; the formal functions are abstractions of the real processes; needed careful consideration of the range of possible values and their probabilities;
- ***subjective judgment*** - occurs due to interpretation of data or behavior

H.M. Regan, M. Colyvan and M.A. Burgman. A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecol. Appl., 12 (2002), pp. 618-628

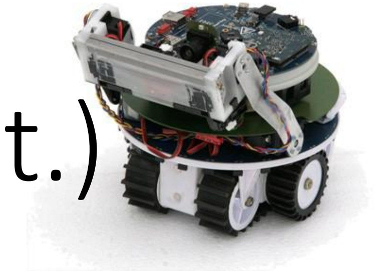
Probabilistic Model Example: POMDP



- *Example:* Awareness Self-Initiation for marXbot
  - marXBot – swarm robotics platform
  - a behavior model based on the *Partially Observable Markov Decision Processes (POMDP)* [Litt_1996]
    - appropriate when there is uncertainty and lack of information needed to determine the state of the entire swarm
    - SC (service component):
      - takes as input *observable* situations, involving other swarm robots and the environment
      - generates as output actions initiating robot activity
    - the generated actions affect the state of the ensemble

M. L. Littman, Algorithms for Sequential Decision Making, PhD Thesis, Department of Computer Science, Brown University, 1996.

Probabilistic Model Example: POMDP(cont.)



Case Study – Swarm of Robots:

- **marXbot*** - a modular research robot equipped with a set of devices to interact with other robots of the swarm or the robotic environment ;
- marXbots robots are able to work in teams where they coordinate based on simple interactions on group tasks.

Example:

a group of marXbots robots may collectively move a relatively heavy object from point ***A*** *to point* ***B*** *by using their grippers.*

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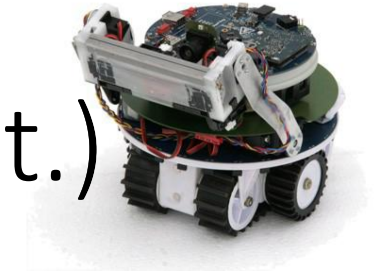
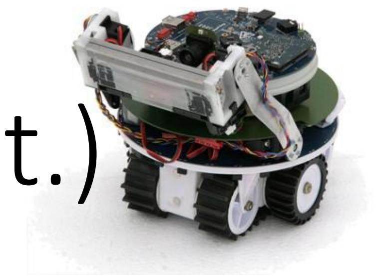
Probabilistic Model Example: POMDP(cont.)



Formal Model – a tuple $\boldsymbol{M = \langle S; A; T; O; R; Z \rangle}$:

- $\boldsymbol{S}$ is a finite set of states;
- An initial belief state $\boldsymbol{s_0 \in S}$ is based on $\boldsymbol{p_0\ (s_0;\ s_0 \in S)}$ **-** a discrete probability distribution over the set of states $\boldsymbol{S}$ (for each state the robot's belief that is currently occupying that state).
- $\boldsymbol{A}$ is a finite set of actions that may be undertaken by the robot.
- $\boldsymbol{T: S \times A \rightarrow \Pi(S)}$ is the state transition function, giving for each swarm state $\boldsymbol{s}$ and robot action $\boldsymbol{a}$, a probability distribution over states. $\boldsymbol{T\ (s;\ a;\ s')}$ computes the probability of ending in state $\boldsymbol{s'}$, given that the start state is $\boldsymbol{s}$ and the robot takes action $\boldsymbol{a}$.
- $\boldsymbol{O: A \times S \rightarrow \Pi(Z)}$ is the observation function giving for each swarm state $\boldsymbol{s}$ and robot action $\boldsymbol{a}$, a probability distribution over observations $\boldsymbol{Z}$. $\boldsymbol{O\ (s';\ a;\ z)}$ is the probability of observing $\boldsymbol{z}$, in state $\boldsymbol{s'}$ after taking action $\boldsymbol{a}$.
- $\boldsymbol{R : S \times A \rightarrow R}$ is a reward function, giving the expected immediate reward gained by the robot for taking an action in a state $\boldsymbol{s}$, e.g., $\boldsymbol{R\ (s;\ a)}$. The reward is a scalar value in the range [0..1] determining, which should be undertaken by the robot in compliance with the swarm goals.

Probabilistic Model Example: POMDP(cont.)



- *Formal Model - Interpretation:*
  - a marXbot swarm is currently occupying the state ***s*** = "*new object to be moved is discovered, but no moving team has been formed yet and still no other marXbot has self-initiated for team formation*";
  - idle marXbot ready to undertake a few actions ***A***, including the action ***a*** = "*self-initiation for team formation*";
  - Reasoning steps:
    - The marXbot computes its current belief state s_0 – the robot picks up the state with the highest probability p_0 and eventually $s_0 = s$.
    - The marXbot computes the probability p_1 of the swarm occupying the state ***s'*** = "*new object is discovered and a marXbot has self-initiated for team formation*" if the action ***a*** is undertaken from state s_0.
    - The marXbot computes the probability $p_2(z \mid s'; a)$ of observation ***z*** = "*there are sufficient numbers of idle marXbots to form a new exploration team*".
    - The marXbot computes the reward $r\,(s_0; a)$ for taking the action ***a*** (*self-initiation for team formation*) in state s_0. If no other immediate actions should be undertaken (forced by other swarm goals), the reward ***r*** should be the highest possible, which will determine the execution of action ***a***.

Probability Computation

probability assessment - an indicator of the number of possible execution paths a robot may take, i. e., the amount of certainty (excess entropy)

Summary

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Probabilistic Model Example – POMDP

Next Lesson – Principles of Probabilistic Programming

Thank You!

Questions?