Försättsblad till skriftlig tentamen vid Linköpings Universitet

Datum för tentamen	2014-01-08
Sal (1) Om tentan går i flera salar ska du bifoga ett försättsblad till varje sal och ringa in vilken sal som avses	TER4
Tid	14-18
Kurskod	TDDC17
Provkod	TEN1
Kursnamn/benämning **Provnamn/benämning**	Artificiell intelligens En skriftlig tentamen
Institution	IDA
Antal uppgifter som ingår i tentamen	8
Jour/Kursansvarig Ange vem som besöker salen	Mariusz Wzorek
Telefon under skrivtiden	0703-887122
Besöker salen ca kl.	kl. 16
Kursadministratör/kontaktperson (namn + tfnr + mailaddress)	Anna Grabska Eklund, ankn. 2362, anna.grabska.eklund@liu.se
Tillåtna hjälpmedel	Miniräknare/Hand calculators
Övrigt	
Vilken typ av papper ska användas, rutigt eller linjerat	Valfritt
Antal exemplar i påsen	

Linköpings Universitet
Institutionen för Datavetenskap
Patrick Doherty

Tentamen
TDDC17 Artificial Intelligence
08 january 2014 kl. 14-18

Points:

The exam consists of exercises worth 38 points.
To pass the exam you need 19 points.

Auxiliary help items:

Hand calculators.

Directions:

You can answer the questions in English or Swedish.
Use notations and methods that have been discussed in the course.
In particular, use the definitions, notations and methods in appendices 1-2.
Make reasonable assumptions when an exercise has been under-specified.
State these assumptions explicitly in your answer.
Begin each exercise on a new page.
Write only on one side of the paper.
Write clearly and concisely.

Jourhavande: Mariusz Wzorek, 0703887122. Mariusz will arrive for questions around 16.00.

1. Based on the material in Chapter 2 of the course book, define succinctly in your own words, the following terms:
   (a) Agent, Agent Function, Agent Program **[1p]**
   (b) Performance Measure, Rationality, Autonomy **[1p]**
   (c) Reflex Agent. Also provide a schematic diagram of such an agent. **[1p]**
   (d) Model-based Agent. Also provide a schematic diagram of such an agent. **[1p]**
   (e) Goal-based Agent. Also provide a schematic diagram of such an agent. **[1p]**

2. Alan Turing proposed the Turing Test as an operational definition of intelligence.
   (a) Describe the Turing Test using your own diagram and explanations.**[2p]**
   (b) Do you believe this is an adequate test for machine intelligence? Justify your answer.**[1p]**

3. Consider the following theory (where x, y and z are variables and history, lottery and john are constants):

$$\forall x([Pass(x, \text{history}) \wedge Win(x, \text{lottery})] \Rightarrow Happy(x)) \tag{1}$$

$$\forall x \forall y([Study(x) \vee Lucky(x)] \Rightarrow Pass(x, y)) \tag{2}$$

$$\neg Study(\text{john}) \wedge Lucky(\text{john}) \tag{3}$$

$$\forall x(Lucky(x) \Rightarrow Win(x, \text{lottery})) \tag{4}$$

   (a) Convert formulas (1) - (4) into clause form. **[1p]**
   (b) Prove that $Happy(\text{john})$ is a logical consequence of (1) - (4) using the resolution proof procedure. **[2p]**
      - Your answer should be structured using a resolution refutation tree (as used in the book).
      - Since the unifications are trivial, it suffices to simply show the binding lists at each resolution step.

4. Constraint satisfaction problems consist of a set of variables, a value domain for each variable and a set of constraints. A solution to a CS problem is a consistent set of bindings to the variables that satisfy the contraints. A standard backtracking search algorithm can be used to find solutions to CS problems. In the simplest case, the algorithm would choose variables to bind and values in the variable's domain to be bound to a variable in an arbitrary manner as the search tree is generated. This is inefficient and there are a number of strategies which can improve the search. Describe the following three strategies:
   (a) Minimum remaining value heuristic (MRV). **[1p]**
   (b) Degree heuristic. **[1p]**
   (c) Least constraining value heuristic. **[1p]**

   Constraint propagation is the general term for propagating constraints on one variable onto other variables. Describe or provide the following:
   (d) What is the Forward Checking technique? **[1p]**
   (e) What is arc consistency? **[1p]**
   (f) Provide a constraint graph that is arc consistent but globally inconsistent. **[1p]**

5. Consider the following example:

   Aching elbows and aching hands may be the result of arthritis. Arthritis is also a possible cause of tennis elbow, which in turn may cause aching elbows. Dishpan hands may also cause aching hands.

   (a) Represent these causal links in a Bayesian network. Let ar stand for "arthritis", ah for "aching hands", ae for "aching elbow", te for "tennis elbow", and dh for "dishpan hands". **[2p]**

   (b) Given the independence assumptions implicit in the Bayesian network, write the formula for the full joint probability distribution over all five variables. **[2p]**

   (c) Compute the following probabilities using the formula for the full joint probability distribution and the probabilities below:

      - $P(ar \mid te, ah)$**[1p]**
      - $P(ar, \neg dh, \neg te, ah, \neg ae)$**[1p]**
      - Appendix 2 provides you with some help in answering these questions.

Table 1: probabilities for question 5.

$$
\begin{aligned}
&P(ah \mid ar, dh) = P(ae \mid ar, te) = 0.1 \\
&P(ah \mid ar, \neg dh) = P(ae \mid ar, \neg te) = 0.99 \\
&P(ah \mid \neg ar, dh) = P(ae \mid \neg ar, te) = 0.99 \\
&P(ah \mid \neg ar, \neg dh) = P(ae \mid \neg ar, \neg te) = 0.00001 \\
&P(te \mid ar) = 0.0001 \\
&P(te \mid \neg ar) = 0.01 \\
&P(ar) = 0.001 \\
&P(dh) = 0.01
\end{aligned}
$$

6. A* search is the most widely-known form of best-first search. The following questions pertain to A* search:

   (a) Explain what an *admissible* heuristic function is using the notation and descriptions in (c). **[1p]**

   (b) Suppose a robot is searching for a path from one location to another in a rectangular grid of locations in which there are arcs between adjacent pairs of locations and the arcs only go in north-south (south-north) and east-west (west-east) directions. Furthermore, assume that the robot can only travel on these arcs and that some of these arcs have obstructions which prevent passage across such arcs.

   The *Manhattan distance* between two locations is the shortest distance between the locations ignoring obstructions. Is the Manhattan distance in the example above an admissible heuristic? Justify your answer explicitly. **[2p]**

   (c) Let $h(n)$ be the estimated cost of the cheapest path from a node n to the goal. Let $g(n)$ be the path cost from the start node n_0 to n. Let $f(n) = g(n) + h(n)$ be the estimated cost of the cheapest solution through n.

   Provide a sufficiently rigid proof that A* is optimal if $h(n)$ is admissible. You need only provide a proof for either tree-search (seminar slides) or graph-search (in course book). If possible, use a diagram to structure the contents of the proof to make it more readable. **[2p]**

7. The following questions pertain to automated planning.

   (a) State three distinct and important reasons why planning should be automated. In other words, why do we want *computers* to create plans, rather than simply creating the plans ourselves? **[1p]**

   (b) Recall that the two heuristic functions $h_1(n)$ and $h_{\mathsf{add}}(n)$ are very similar, but that their definitions have one crucial difference that results in significant differences in their behavior. What is this crucial difference? Which of the functions is inadmissible, and why? Which function provides more information, and why? **[2p]**

   (c) Plan-space search begins with an *initial plan* and iteratively modifies this plan in order to repair *flaws.* Name the two distinct *types* of flaw that exist. Explain clearly how these flaw types can be identified in a plan. For the explanation to be sufficiently clear, you may need to provide an example plan drawn in the same way as during the lectures. **[2p]**

8. The following questions pertain to machine learning. Give detailed answers.

   (a) Explain supervised and reinforcement learning in terms of the input and output of the respective types of algorithms, highlighting their differences. **[2p]**

   (b) Explain the concept of *overfitting* and a princpled way to detect it. **[1p]**

   (c) Explain when and why *exploration* is needed and outline an example algorithm. **[1p]**

Appendix 1

Converting arbitrary wffs to CNF form

1. Eliminate implication signs.
2. Reduce scopes of negation signs.
3. Standardize variables within the scopes of quantifiers (Each quantifier should have its own unique variable).
4. Eliminate existential quantifiers. This may involve introduction of Skolem constants or functions.
5. Convert to prenex form by moving all remaining quantifiers to the front of the formula.
6. Put the matrix into conjunctive normal form. Two useful rules are:
   - $\omega_1 \vee (\omega_2 \wedge \omega_3) \equiv (\omega_1 \vee \omega_2) \wedge (\omega_1 \vee \omega_3)$
   - $\omega_1 \wedge (\omega_2 \vee \omega_3) \equiv (\omega_1 \wedge \omega_2) \vee (\omega_1 \wedge \omega_3)$
7. Eliminate universal quantifiers.
8. Eliminate $\wedge$ symbols.
9. Rename variables so that no variable symbol appears in more than one clause.

Skolemization

Two specific examples. One can of course generalize the technique.
$\exists x P(x)$:
Skolemized: $P(\mathsf{c})$ where c is a fresh constant name.
$\forall x_1, \ldots, x_k, \exists y P(y)$:
Skolemized: $P(\mathsf{f}(x_1, \ldots, x_k))$, where f is a fresh function name.

Appendix 2

A generic entry in a joint probability distribution is the probability of a conjunction of particular assignments to each variable, such as $P(X_1 = x_1 \wedge \ldots \wedge X_n = x_n)$. The notation $P(x_1, \ldots, x_n)$ can be used as an abbreviation for this.

The chain rule states that any entry in the full joint distribution can be represented as a product of conditional probabilities:

$$P(x_1, \ldots, x_n) = \prod_{i=1}^{n} P(x_i \mid x_{i-1}, \ldots, x_1) \tag{5}$$

Given the independence assumptions implicit in a Bayesian network a more efficient representation of entries in the full joint distribution may be defined as

$$P(x_1, \ldots, x_n) = \prod_{i=1}^{n} P(x_i \mid \mathit{parents}(X_i)), \tag{6}$$

where $\mathit{parents}(X_i)$ denotes the specific values of the variables in $\mathit{Parents}(X_i)$.

Recall the following definition of a conditional probability:

$$\mathbf{P}(X \mid Y) = \frac{\mathbf{P}(X \wedge Y)}{\mathbf{P}(Y)} \tag{7}$$

The following is a useful general inference procedure:

Let X be the query variable, let $\mathbf{E}$ be the set of evidence variables, let $\mathbf{e}$ be the observed values for them, let $\mathbf{Y}$ be the remaining unobserved variables and let α be the normalization constant:

$$\mathbf{P}(X \mid \mathbf{e}) = \alpha \mathbf{P}(X, \mathbf{e}) = \alpha \sum_{\mathbf{y}} \mathbf{P}(X, \mathbf{e}, \mathbf{y}) \tag{8}$$

where the summation is over all possible $\mathbf{y}$'s (i.e. all possible combinations of values of the unobserved variables $\mathbf{Y}$).

Equivalently, without the normalization constant:

$$\mathbf{P}(X \mid \mathbf{e}) = \frac{\mathbf{P}(X, \mathbf{e})}{\mathbf{P}(\mathbf{e})} = \frac{\sum_{\mathbf{y}} \mathbf{P}(X, \mathbf{e}, \mathbf{y})}{\sum_{\mathbf{x}} \sum_{\mathbf{y}} \mathbf{P}(\mathbf{x}, \mathbf{e}, \mathbf{y})} \tag{9}$$