Information about the exam

- 1. The exam has 6 sections of questions. They consist of both multiple choice questions and free text questions.
- 2. The total number of points for the exam is 48 and a passing grade is at most 25. Grade 4 is at most 34 points and Grade 5 is at most 41 points. The limits will be modify based on the results, but they will not be higher.
- 3. For multiple choice questions you will get a positive score for each correct choice and a negative score for each incorrect choice. They are both the same, usually 0.5 or 1. This means that it may be an idea to only check those choices you are certain about. You cannot get a negative score.
- 4. The free text questions are designed so that text should be enough to answer them. There are limited formatting facilities that can be used to format and structure your answers. For instance, there is a table facility and special character facility. These features are accessible via icons at the top of the answer textbox.
- 5. A scientific calculator is accessible for the Bayesian Network question and in the Resource section.
- 6. Both the course textbook and the lecture slides are accessible from the Resource section at the end of the exam. Simply click on a link and a new tab will be generated in the browser where you can read the selected material.
- 7. Please make reasonable assumptions if you believe an exercise is under specified and state those assumptions explicitly in your answer.
- 8. Your answers should be clear, concise and compact.
- $9. \ Fredrik \ will \ visit \ the \ exam \ rooms \ around \ 9.45 \ to \ provide \ clarifications \ if \ needed \ for \ the \ exam \ questions.$

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1. Logic	
a) List all models of $\varphi = ((A \lor \neg B) \land (A \to (C \land \neg B)))$ over the propositions $\Sigma = \{A,B,C\}$. Does $\neg B$ logically follow from P and P are the propositions of P and P are the proposition of P are the proposition of P and P are the proposition of P are the proposition of P are the proposition of P and P are the proposition of P are the proposition of P and P are the proposition of P and P are the proposition of P are the proposition of P are the proposition of P and P are the proposition of P and P are the proposition of P are the propo	om
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b) Use the equivalences introduced in the lecture to bring the formula $\psi = ((A \lor \neg B) \to C)$ into onjunctive normal form (CNF). Use only one equivalence per step. (2p)	
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c) Use DPLL to find a satisfying assignment for $\Delta = \{\{X, Y\}, \{\neg Y, Z\}, \{\neg X, \neg Y, \neg Z\}, \{\neg X, Y, \neg Z\}\}.$	
ry variables in the order X, Y,Z and truth values in the order T,F.	
pecify the list of clauses after every modification.	
elearly specify the recursive call structure of the algorithm, for example by using a nested list or labeling steps as a, 2b, 1b ". (5p)	s "1a
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Sektion 3

2. Bayesian Networks

Consider the following problem 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. Let AR stand for "arthritis", AH for "aching hands", AE for "aching elbow", TE for "tennis elbow", and DH for "dishpan hands".

P(ah|ar, dh) = P(ae|ar, te) = 0.2

 $P(ah|ar, \neg dh) = P(ae|ar, \neg te) = 0.8$

 $P(ah|\neg ar, dh) = P(ae|\neg ar, te) = 0.8$

 $P(ah|\neg ar, \neg dh) = P(ae|\neg ar, \neg te) = 0.1$

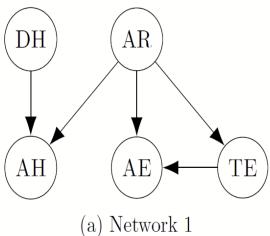
P(te|ar) = 0.1

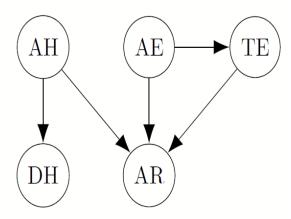
 $P(te|\neg ar) = 0.1$

P(ar) = 0.02

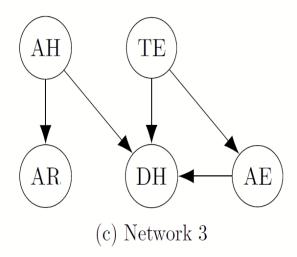
P(dh) = 0.02

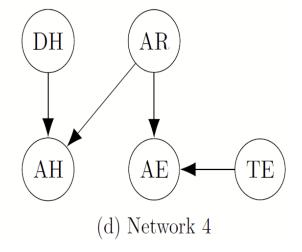
2a) Which of the following Bayesian networks represent the causal links described in the problem example defined above? (1p)





(b) Network 2





Network 1 □ Network 2

□ Network 3

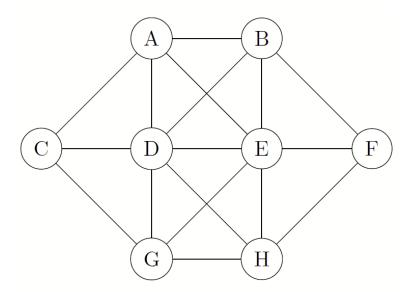
Network 4

	2b) Given the independence assumptions implicit in the Bayesian network, which of the formulas below represent the full joint probability distribution over all five variables, i.e. P(AR,AH,AE,TE,DH) =? (1p)	er
2c) Using the formula for the full joint probability distribution and the probabilities given in the table above select statements which are True: (4p)	$ \ \ \square \ P(AR) \cdot P(AH AR,DH) \cdot P(AE AR,TE) \cdot P(TE) \cdot P(DH) $	
probabilities given in the table above select statements which are True: (4p) $P(\neg ar, \neg dh, \neg te, ah, \neg ae) = 0.98 \cdot 0.98 \cdot 0.1 \cdot 0.8 \cdot 0.8 = 0.061466$ $P(\neg ar, \neg dh, \neg te, ah, \neg ae) = 0.98 \cdot 0.98 \cdot 0.9 \cdot 0.1 \cdot 0.9 = 0.07779$ $P(ar ah, te) = \alpha \cdot \sum_{DH, AE} P(ar, ah, te, DH, AE), \text{ where } \alpha \text{ is the normalization factor.}$ $P(ar ah, te) = \alpha \cdot \sum_{AR, DH, AE} P(AR, ah, te, DH, AE), \text{ where } \alpha \text{ is the normalization factor.}$ $P(ar ah, te) = 0.1236$ $P(ar ah, te) = 0.0697$ $P(ar, dh, ah, te) = \sum_{AE} P(ar, ah, te, dh, AE)$ $P(ar, dh, ah, te) = \alpha \cdot \sum_{AE} P(ar, ah, te, dh, AE), \text{ where } \alpha \text{ is the normalization factor.}$ This space is available for comments and/or assumptions that you wish to state.		•
$ P(\neg ar, \neg dh, \neg te, ah, \neg ae) = 0.98 \cdot 0.98 \cdot 0.9 \cdot 0.1 \cdot 0.9 = 0.07779 $ $ P(ar ah, te) = \alpha \cdot \sum_{DH, AE} P(ar, ah, te, DH, AE), \text{ where } \alpha \text{ is the normalization factor.} $ $ P(ar ah, te) = \alpha \cdot \sum_{AR, DH, AE} P(AR, ah, te, DH, AE), \text{ where } \alpha \text{ is the normalization factor.} $ $ P(ar ah, te) = 0.1236 $ $ P(ar ah, te) = 0.0697 $ $ P(ar, dh, ah, te) = \sum_{AE} P(ar, ah, te, dh, AE) $ $ P(ar, dh, ah, te) = \alpha \cdot \sum_{AE} P(ar, ah, te, dh, AE), \text{ where } \alpha \text{ is the normalization factor.} $ This space is available for comments and/or assumptions that you wish to state. $ 0 / 10000 \text{ Word Limit} $		
P(ar ah, te) = $\alpha \cdot \sum_{DH, AE}$ P(ar, ah, te,DH,AE), where α is the normalization factor. P(ar ah, te) = $\alpha \cdot \sum_{AR, DH, AE}$ P(AR, ah, te,DH,AE), where α is the normalization factor. P(ar ah, te) = 0.1236 P(ar ah, te) = 0.0697 P(ar, dh, ah, te) = \sum_{AE} P(ar, ah, te, dh,AE) P(ar, dh, ah, te) = $\alpha \cdot \sum_{AE}$ P(ar, ah, te, dh, AE), where α is the normalization factor. This space is available for comments and/or assumptions that you wish to state.	□ P(¬ar, ¬dh,¬te, ah,¬ae) = 0.98 · 0.98 · 0.1 · 0.8 · 0.8 = 0.061466	
normalization factor. $P(ar ah, te) = \alpha \cdot \sum_{AR, DH, AE} P(AR, ah, te, DH, AE), \text{ where } \alpha \text{ is the normalization factor.}$ $P(ar ah, te) = 0.1236$ $P(ar ah, te) = 0.0697$ $P(ar, dh, ah, te) = \sum_{AE} P(ar, ah, te, dh, AE)$ $P(ar, dh, ah, te) = \alpha \cdot \sum_{AE} P(ar, ah, te, dh, AE), \text{ where } \alpha \text{ is the normalization factor.}$ This space is available for comments and/or assumptions that you wish to state.	□ P(¬ar, ¬dh,¬te, ah,¬ae) = 0.98 · 0.98 · 0.9 · 0.1 · 0.9 = 0.07779	•
normalization factor. $P(ar ah, te) = 0.1236$ $P(ar ah, te) = 0.0697$ $P(ar, dh, ah, te) = \sum_{AE} P(ar, ah, te, dh, AE)$ $P(ar, dh, ah, te) = \alpha \cdot \sum_{AE} P(ar, ah, te, dh, AE), \text{ where } \alpha \text{ is the normalization factor.}$ This space is available for comments and/or assumptions that you wish to state.	·	•
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□ P(ar, dh, ah, te) = \sum_{AE} P(ar, ah, te, dh, AE), where α is the normalization factor. This space is available for comments and/or assumptions that you wish to state.	□ P(ar ah, te) = 0.1236	•
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normalization factor. This space is available for comments and/or assumptions that you wish to state. 0 / 10000 Word Limit	\square P(ar, dh, ah, te) = \sum_{AE} P(ar, ah, te, dh, AE)	~
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■ Calculator	0 / 10000 Word Limit	t
	☐ Calculator	

3. CSP

The following questions pertain to Constraint Satisfaction Problems (CSPs). CSPs 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 constraints.

The figure below shows a constraint graph with eight variables. The value domains for each variable are the integer numbers 1 to 8. The constraints state that adjacent/connected nodes can not have consecutive numbers and they must be different. For example, if node C is labeled 2, then nodes A, D, and G cannot be labeled with either 1 or 3 (consecutive numbers) or 2 (the same number).



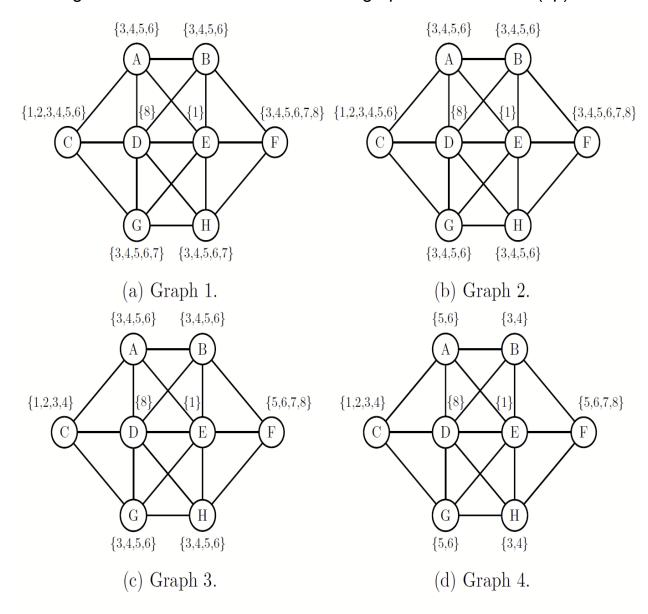
Constraint graph.

3a) Select statements which are True? (1p)

Applying Degree Heuristic to a CSP selects a variable which is involved in the largest number of constraints on other unassigned variables.	•
Applying Degree Heuristic to a CSP selects a variable with the fewest possible bindings left.	
If we apply the Degree Heuristic to the constraint graph defined in the figure above, C and F nodes will be chosen as potential candidates for labeling.	!
If we apply the Degree Heuristic to the constraint graph defined in the figure above, D and E nodes will be chosen as potential candidates for labeling.	•

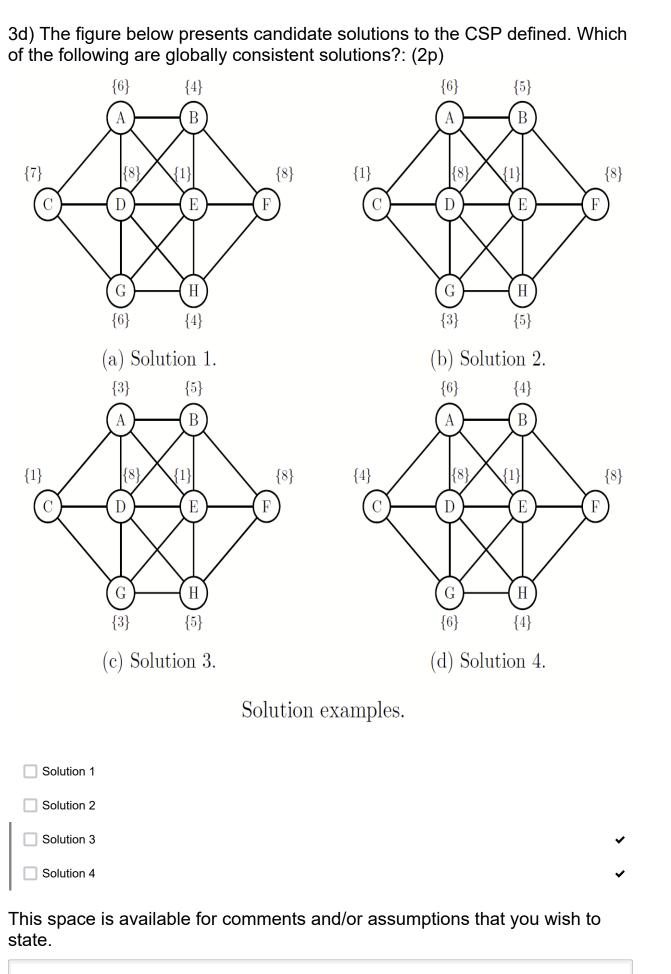
3b) Select statements which are True: (1p)	
Applying Least Constraining Value Heuristic to a CSP selects a value for chosen variable that rules out the fewest choices for the neighboring variables in the constraint graph.	→
Applying Least Constraining Value Heuristic to a CSP selects a value for chosen variable that yields the lowest number of consistent values in the neighboring variables in the constraint graph.	
Assuming a variable was chosen using the Degree Heuristic in the previous question, the Least Constraining Value Heuristic will select 2, 3, 4, 5, 6, and 7 as the potential candidate values.	
Assuming a variable was chosen using the Degree Heuristic in the previous question, the Least Constraining Value Heuristic will select 1 and 8 as the potential candidate values.	~

3c) Suppose node D = 8, node E = 1 and nodes A,B,C,F,G,H are labeled 1,2,3,4,5,6,7,8. Which of the following graphs will be the result of applying the AC-3 algorithm which makes the constraint graph arc consistent. (2p)



Potential constraint graphs after applying AC-3.

- O Graph 1
- O Graph 2
- Graph 3
- O Graph 4
- None of the graphs



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4. Search

Consider the game tree in the figure below in which the leaf nodes show heuristic values and where all heuristic values are from the MAX players point of view. Assume search is in the left to right direction.

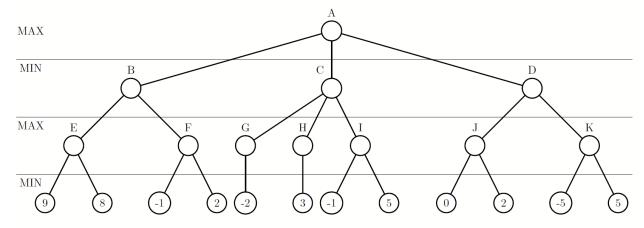


Figure 5: Two player game search

4a) Apply the MinMax algorithm to the game tree in the figure and state what
move the first player (maximiser) would make. Provide heuristic values for
each node in form of a table or text (e.g. A: value, B: value etc.). (2p)

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4b) In the game tree above, what nodes would not need to be examined using the alphabeta pruning procedure? Justify your answer in terms of the relevant α/β values in the nodes of the tree and why certain branches would be cutoff based on this evaluation.

Use annotation similar to the question above. To describe edges use one of the following notations: "second edge below X" or "edge between X and Y"). (2p)

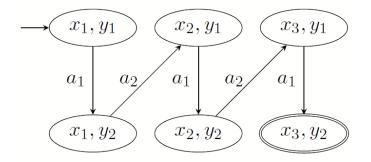


4c) A* search is the most widely-known form of best-first search. Suppose a robot is searching for a path from one location to another in a rectangular grid of locations in which there are arcs between adjacent pairs of locations and the arcs only go in north-south (south-north) and east-west (west-east) 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. (2p)
4d) Which of the following are true and which are false? Explain your answers. I. Depth-first search always expands at least as many nodes as A* search with an admissible heuristic. (1p) II. Heuristic function h(n) = 0 is an admissible heuristic for the 8-puzzle game. (1p) III. Breadth-first search is complete even if zero step costs are allowed. (1p)
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5.	Planning	

J.	Planning				
			nswer. In total you can g	•	
	□ The state-space induced by a planning task Π can be exponentially larger than the encoding of Π. ✓				
	The main difference be	etween STRIPS task	s and SAS+ tasks is the	size of the variable domains.	~
	In SAS+ conditions are	represented by con	nplete states.		
	Some tasks require mu	ılti-valued variables	and can thus only be en	coded in SAS+.	
5b) W	Vhich of the following	g statements abo	ut planning heuristic	s are true? (2p)	
	For optimal planning, w	ve want heuristics to	be admissible.		~
	Every relaxed plan is a	plan.			
A PDB heuristic with a pattern containing n binary variables can be precomputed and stored in space linear in n.					
		pattern containing n	i binary vanabies san be	,	
ı	linear in n.		is equal to the perfect h		•
5c) Cc	linear in n. It is possible to create a	a PDB heuristic that f the following STRIF	is equal to the perfect h		~
5c) Cc	linear in n. It is possible to create a omplete the definition of	a PDB heuristic that f the following STRIF	is equal to the perfect h	euristic h∗.	~
5c) Cc $\Pi = \langle V \rangle$ $a = a_1$	linear in n. It is possible to create a complete the definition of Y , I, G,A Y with $Y = \{x, y\}$,	a PDB heuristic that the following STRIF $I = \emptyset$, $G = \{x, y\}$, A	is equal to the perfect h PS planning task so that = {a1, a2}, and	euristic h∗. its optimal plan has length 3 and	~
5c) Cc Π = ⟨V	linear in n. It is possible to create a complete the definition of Y , I, G,A Y with $Y = \{x, y\}$,	a PDB heuristic that the following STRIF $I = \emptyset$, $G = \{x, y\}$, A	is equal to the perfect h PS planning task so that = {a1, a2}, and	euristic h∗. its optimal plan has length 3 and	~
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5c) Cc $\Pi = \langle V \rangle$ $a = a_1$	linear in n. It is possible to create a complete the definition of Y , I, G,A Y with $Y = \{x, y\}$,	a PDB heuristic that the following STRIF $I = \emptyset$, $G = \{x, y\}$, A	is equal to the perfect h PS planning task so that = {a1, a2}, and	euristic h \star . its optimal plan has length 3 and $cost(a)$	cost 5. (3p)
5c) Cc $\Pi = \langle V \rangle$ $a = a_1$	linear in n. It is possible to create a complete the definition of Y , I, G,A Y with $Y = \{x, y\}$,	a PDB heuristic that the following STRIF $I = \emptyset$, $G = \{x, y\}$, A	is equal to the perfect h PS planning task so that = {a1, a2}, and	euristic h \star . its optimal plan has length 3 and $cost(a)$	cost 5. (3p)

5d) Consider the abstraction of the following state space that is induced by the projection $\pi\{X\}$ to the variable X. Give the heuristic value of the pattern database heuristic h $\{X\}$ for each state in the original state space. A state label of x, y corresponds to state $\{X \ 7 \rightarrow x, \ Y \ 7 \rightarrow y\}$ and all actions have a cost of 1. (3p)



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6. Machine Learning	
6a) Explain the main components of a neural n a supervised manner. (3p)	etwork and how it is trained in
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6b) What is the Q-function in reinforcement lea selecting the optimal action? (2p)	rning and how is it related to
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6c) What is the XOR-problem in relation to the	perceptron? (1p)
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6d) What is regularization in supervised learnin	ng? (1p)
6d) What is regularization in supervised learnin	ng? (1p)

Resources

The chapters of the course book are available here:

- Preface: Preface.pdf
- Chapter 1 Introduction: Chapter 1.pdf
- Chapter 2 Intelligent Agents: Chapter 2.pdf
- Chapter 3 Solving Problems by Searching: Chapter 3.pdf
- Chapter 4 Search in Complex Environments: Chapter 4.pdf
- Chapter 5 Constraint Satisfaction Problems: Chapter 5.pdf
- Chapter 6 Adversarial Search and Games: Chapter 6.pdf
- Chapter 7 Logical Agents: Chapter 7.pdf
- Chapter 8 First-Order Logic: Chapter 8.pdf
- Chapter 9 Inference in First-Order Logic: Chapter 9.pdf
- Chapter 10 Knowledge Representation: Chapter 10.pdf
- Chapter 11 Automated Planning: Chapter 11.pdf
- Chapter 12 Quantifying Uncertainty: Chapter 12.pdf
- Chapter 13 Probabilistic Reasoning: Chapter 13.pdf
- Chapter 14 Probabilistic Reasoning over Time: Chapter 14.pdf
- Chpater 15 Making Simple Decisions: Chapter 15.pdf
- Chapter 16 Making Complex Decisions: Chapter 16.pdf
- Chpater 17 Multiagent Decision Making: Chapter 17.pdf
- Chapter 18 Probabilistic Programming: Chapter 18.pdf
- Chapter 19 Learning from Examples: Chapter 19.pdf
- Chapter 20 Knowledge in Learning: Chapter 20.pdf
- Chapter 21 Learning Probabilistic Models: Chapter 21.pdf
- Chapter 22 Deep Learning: Chapter 22.pdf
- Chapter 23 Reinforcement Learning (from 3rd ed): Chapter 23 3rd ed.pdf
- Appendix A: <u>Appendix A.pdf</u>
 Bibliography: <u>Bibliography.pdf</u>

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Lecture notes

- LE1 Course Introduction, History of AI: 2023-08-29-LE1-Introduction to AI.pdf
- LE2 Search I: 2023-08-31-LE2-Search I.pdf
- LE3 Search II: 2023-09-04-LE3-Search II.pdf
- LE4 Constraint Satisfaction: 2023-09-05-LE4-CSP.pdf
- LE5 Machine Learning I: 2023-09-08-LE5 ML I.pdf
- LE6 Machine Learning II: 2023-09-11-LE6 ML II.pdf
- LE7 Machine Learning III: 2023-09-12-LE7 ML III.pdf
- LE8 Knowledge Representation I: TDDC17_Le8_logic1.pdf
- LE9 Knowledge Representation II: TDDC17_Le9_logic2.pdf
- LE10 Knowledge Representation III: <u>TDDC17_Le10_logic3.pdf</u>
- LE11 Bayesian Networks: 2023-09-22-LE11-Bayesian Networks.pdf
- LE12 Planning I: TDDC17_Le12_planning1.pdf TDDC17_Le12_planning2.pdf
- LE13 Planning II: TDDC17_Le13_planning3.pdf TDDC17_Le13_planning4.pdf
- LE14 Planning III: TDDC17_Le14_planning5.pdf TDDC17_Le14_planning6.pdf
- LE15 Robotics/Perception I: TDDC17_Le15_robotics1.pdf
- LE16 Robotics/Perception II: TDDC17_Le16_robotics2.pdf
- LE17 Course Summary: 2023-10-06 LE17 Exam questions.pdf

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