COMP3308/3608 Introduction to Artificial Intelligenece (regular and advanced)
semester 1, 2020

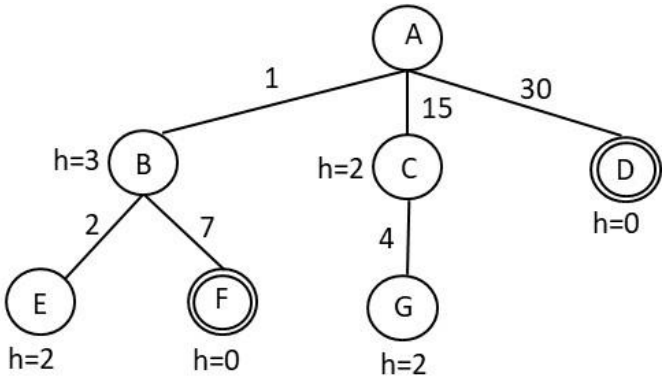
Information about the exam

- The exam will be online, via Canvas, un-proctored. It is set as a Quiz.
- The Canvas site for the exam is different that the Canvas site we use during the semester. There are 2 exam sites: one for COMP3308 called "Final Exam for COMP3308" and another one for COMP3608 - "Final Exam for COMP3608". The Exams Office will give you access to your exam site.
- Students who are not in Australia and are in different time zones may apply for special arrangements for the exam:
  https://www.sydney.edu.au/students/special-consideration.html#time-zone
- The duration of the exam is standard: 2 hours + 10 minutes reading time = 130 min. The Canvas Quiz will open at the scheduled time (as per your exam timetable) and close after 130 mins.
- The exam is worth 60 marks (=60% of your final mark). To pass the course you need at least 40% on the exam (i.e. 24 marks), regardless of what your mark during the semester is.
- All material is examinable except week 1, week 13a (recommender systems), historical context, Matlab and Weka.
- Tip: Have a calculator ready as there are some calculation questions.
- There are 3 types of questions: 1) problem solving, 2) questions requiring short answers, and 3) multiple-choice questions (a small number).

Sample exam questions

In addition to these questions please also see on Canvas:
Search: Quiz_Practice _with_Quokkas.pdf
Bayesian networks: BN_practice_questions.pdf

Question 1. In the tree below the step costs are shown along the edges and the h values are shown next to each node. The goal nodes are double-circled: F and D.



Write down the order in which nodes are expanded using:

a) Breadth-first search
b) Depth-first search
c) Uniform cost search
d) Iterative deepening search
e) Greedy search
f) A*

In case of ties, expand the nodes in alphabetical order.

Solution:

a) Breadth-first search: ABCD
b) Depth-first search: ABEF
c) Uniform cost search: ABEF
d) Iterative deepening search:AABCD
e) Greedy search: AD
f) A*: ABEF

Review and explanation:

- BFS: Expands the shallowest unexpanded node
- DFS: Expands the deepest unexpanded node
- UCS: Expands the node with the smallest path cost *g(n)*

- IDS: DFS at levels l = 0, 1, 2, etc. Expands the deepest unexpanded node within level l
- Greedy: Expands the node with the smallest heuristic value *h(n)*
- A*: Expands the node with the smallest *f(n)=g(n)+h(n)*

Question 2. Answer briefly and concisely:

a) A* uses admissible heuristics. What happens if we use a non-admissible one? Is it still useful to use A* with a non-admissible heuristic?

b) What is the advantage of choosing a dominant heuristic in A* search?

c) What is the main advantage of hill climbing search over A* search?

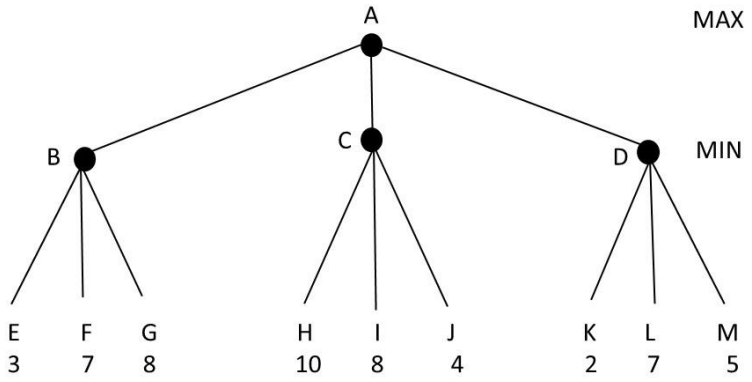
Answers:

a) Not optimal anymore. But it could still find a reasonably good solution in acceptable time, depending on how good the heuristic is.

b) Fewer nodes expanded. As a result, the optimal solution will be found quicker.

c) Space complexity – keeps only the current node in memory.

Question 3. Consider the following game in which the evaluation function values for player MAX are shown at the leaf nodes. MAX is the maximizing player and MIN is the minimizing player. The first player is MAX.



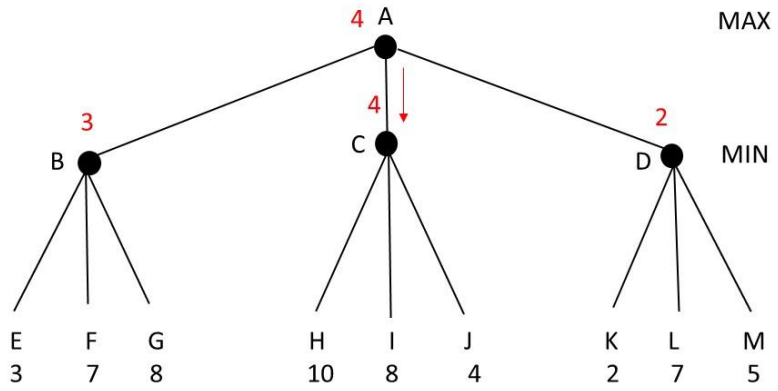
a) What will be the backed-up value of the root node computed by the minimax algorithm?

b) Which move should MAX choose based on the minimax algorithm – to node B, C or D?

c) Assume that we now use the alpha-beta algorithm. List all branches that will be pruned, e.g. AB etc. Assume that the children are visited left-to-right (as usual).

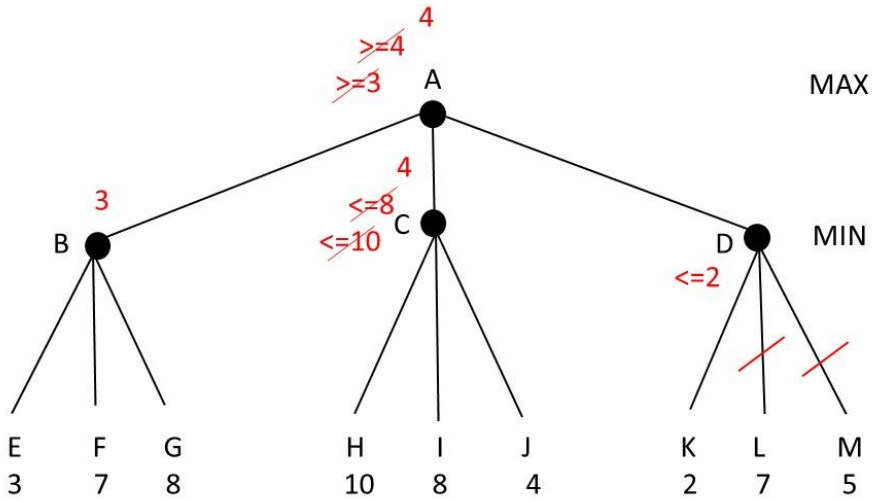
Solution:

a) The value of A is 4:



b) To node C

c) LD and MD will be pruned:



Question 4. Answer briefly and concisely:

a) The 1R algorithm generates a set of rules. What do these rules test?

b) *Gain ratio* is a modification of *Gain* used in decision trees. What is its advantage?

c) Propose two strategies for dealing with missing attribute values in learning algorithms.

d) Why do we need to normalize the attribute values in the k-nearest-neighbor algorithm?

e) What is the main limitation of the perceptrons?

f) Describe an early stopping method used in the backpropagation algorithm to prevent overfitting.

g) The problem of finding a decision boundary in support vector machine can be formulated as an optimisation problem using Lagrange multipliers. What are we maximizing?

h) In linear support vector machines, we use dot products both during training and during classification of a new example. What vectors are these products of?

During training:

During classification of a new example:

Answers:

a) They test the values of a single attribute.

b) It penalizes highly-branching attributes by taking into account the number and the size of branches.

c) Strategy 1: Use the attribute mean to fill in the missing value.
Strategy 2: Use the attribute mean for all examples belonging to the same class.

d) As different attributes are measured on different scales, without normalization the effect of the attributes with smaller scale of measurement will be less significant than those with larger.

e) Can separate only linearly separable data.

f) Available data is divided into 3 subsets:
Training set – used for updating the weights.
Validation set – used for early stopping.
Training is stopped when the error on the validation set increases for a pre-specified number of iterations.

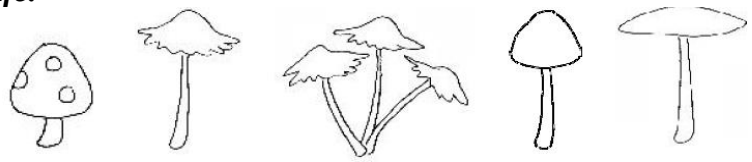
g) The margin of the hyperplane.

h) During training: Pairs of training examples.
During classification of a new example: The new example and the support vectors.

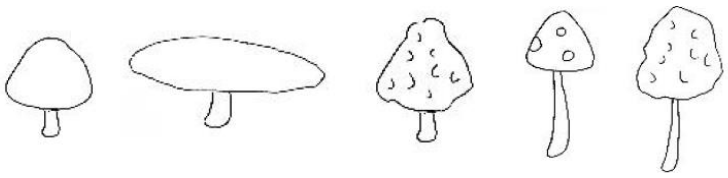
Question 5. Consider the task of learning to classify mushrooms as ***safe*** or ***poisonous*** based on the following four features: stem = {short, long}, bell = {rounded, flat}, texture = {plain, spots, bumpy, ruffles} and number = {single, multiple}.

The training data consists of the following 10 examples:

Safe:



Poisonous:



a) Use Naïve Bayes to predict the class of the following new example:

Show your calculations.

b) How would 3-Nearest Neighbor using the Hamming distance classify the same example as above?

c) Consider building a decision tree. Calculate the information gain for ***texture*** and ***number.*** Which one of these two features will be selected?

You may use this table:

x	y	$-(x/y)*\log_2(x/y)$	x	y	$-(x/y)*\log_2(x/y$	x	y	$-(x/y)*\log_2(x/y$	x	y	$-(x/y)*\log_2(x/y$
1	2	0.50	4	5	0.26	6	7	0.19	5	9	0.47
1	3	0.53	1	6	0.43	1	8	0.38	7	9	0.28
2	3	0.39	5	6	0.22	3	8	0.53	8	9	0.15
1	4	0.5	1	7	0.40	5	8	0.42	1	10	0.33
3	4	0.31	2	7	0.52	7	8	0.17	3	10	0.52
1	5	0.46	3	7	0.52	1	9	0.35	7	10	0.36
2	5	0.53	4	7	0.46	2	9	0.48	9	10	0.14
3	5	0.44	5	7	0.35	4	9	0.52			

d) Consider a single perceptron for this task. What is the number of inputs? What is the dimensionality of the weight space?

Note: The training data and new example will be given to you in a table, you are not expexted to derive them from pictures during the exam.

The training data is:

n	**stem**	**bell**	**texture**	**number**	**class**
1	short	rounded	spots	single	safe
2	long	flat	ruffles	single	safe
3	long	flat	ruffles	multiple	safe
4	long	rounded	plain	single	safe
5	long	flat	plain	single	safe
6	short	rounded	plain	single	poisonous
7	short	flat	plain	single	poisonous
8	short	rounded	bumpy	single	poisonous
9	long	rounded	spots	single	poisonous
10	long	rounded	bumpy	single	poisonous

The new example is: stem=long, bell=flat, texture=spots, number=single

a) Naïve Bayes:

The new example is the evidence E.
E1=stem=long, E2=bell=flat, E3=texture=spots, E4=number=single

We need to compute P(safe|E) and P(poisonous|E) and compare them.

$$P(safe \mid E) = \frac{P(E1 \mid safe)\, P(E2 \mid safe)\, P(E3 \mid safe) P(E4 \mid safe) P(safe)}{P(E)}$$

P(safe)=5/10=1/2
P(E1|safe)=P(stem=long|safe)=4/5
P(E2|safe)=P(bell=flat|safe)=3/5
P(E3|safe)=P(texture=spots|safe)=1/5
P(E4|safe)=P(number=single|safe)=4/5

$$P(safe \mid E) = \frac{\frac{4}{5}\frac{3}{5}\frac{1}{5}\frac{4}{5}\frac{1}{2}}{P(E)} = \frac{\frac{24}{625}}{P(E)}$$

P(poisonous)=5/10=1/2
P(E1|poisonous)=P(stem=long|poisonous)=2/5
P(E2|poisonous)=P(bell=flat|poisonous)=1/5
P(E3|poisonous)=P(texture=spots|poisonous)=1/5
P(E4|poisonous)=P(number=single|poisonous)=5/5

$$P(poisonous \mid E) = \frac{\frac{2}{5}\frac{1}{5}\frac{1}{5}\frac{5}{5}\frac{1}{2}}{P(E)} = \frac{\frac{5}{625}}{P(E)}$$

=> Naïve Bayes predicts ***safe***.

b) The three nearest neighbors have a distance of 1 and are examples 2, 5 and 9:

The vote is 2:1 in favour of ***safe.***

c) Decision tree

H(S)=I(5/10,5/10)= 1 bit

Split on ***texture***:
$H(S_{spots})$=I(1/2,1/2)=1 bit
$H(S_{ruffles})$=I(2/2,0/2)=0 bits
$H(S_{plain})$=I(2/4,2/4)=1 bit
$H(S_{bumpy})$=I(0/2,2/2)=0 bits
H(S|texture)=2/10*1 + 2/10*0 + 4/10*1 + 2/10*0=6/10=0.6 bits
gain(texture)=1-0.6=0.4 bits

Split on ***number***:
$H(S_{single})$=I(4/9,5/9)=-4/9log4/9-5/9log5/9=0.52+0.47=0.99 bits
$H(S_{multiple})$=I(1/1,0/1)=0 bits
H(S|number)=9/10*0.99 + 1/10*0=0.891 bits
gain(number)=1-0.891=0.109 bits

gain(texture) > gain(number) => ***texture*** will be selected (if we have to choose between ***texture*** and ***number***)

d) There should be 10 inputs, 1 for each attribute value. This means using binary encoding of the attributes and their values (e.g. 10 for ***stem=short*** and 01 for ***stem=long***). Binary encoding is the most popular encoding for nominal attributes.

The weight space has a dimensionality of 11 (10 +1 bias weight).

Question 6. Given the training data in the table below where *credit history*, *debt*, *collateral* and *income* are attributes and *risk* is the class, predict the class of the following new example using the 1R algorithm: *credit history=unknown, debt=low, collateral=none, income=15-35K.* Show your calculations.

credit history	debt	collateral	income	risk
bad	high	none	0-15k	high
unknown	high	none	15-35k	high
unknown	low	none	15-35k	moderate
unknown	low	none	0-15k	high
unknown	low	none	over 35k	low
unknown	low	adequate	over 35k	low
bad	low	none	0-15k	high
bad	low	adequate	over 35k	moderate
good	low	none	over 35k	low
good	high	adequate	over 35k	low
good	high	none	0-15k	high
good	high	none	15-35k	moderate
good	high	none	over 35k	low
bad	high	none	15-35k	high

Solution:
1. Attribute *credit history*
bad:0 low, 1 moderate, 3 high => risk=high, errors: 1/4
unknown: 2 low, 1 moderate, 2 high => risk=low, errors: 3/5
good: 3 low, 1 moderate, 1 high => risk=low, errors: 2/5
total errors: 6/14

2. Attribute *debt*
high: 2 low, 1 moderate, 4 high => risk=high, errors: 3/7
low: 3 low, 2 moderate, 2 high => risk=low, errors: 4/7
total errors: 7/14

3. Attribute *collateral*
none: 3 low, 2 moderate, 6 high => risk=high, errors: 5/11
adequate: 2 low, 1 moderate, 0 high => risk=low, errors: 1/3
total errors: 6/14

4. Attribute *income*
0-15K: 0 low, 0 moderate, 4 high => risk=high, errors: 0/6
15-35K: 0 low, 2 moderate, 2 high => risk=moderate, errors: 2/4
over 35K: 5 low, 1 moderate, 0 high => risk=low, errors: 1/6
total errors: 3/14

The rule based on the attribute *income* has the minimum number of errors =>1R produces the following rule:

if income=0-15K then risk=high
else if income=15-35K then risk=moderate
else if income=over 35K then risk=low

The new example has *income=15*-35K and will be classified as *risk=moderate*.

Question 7. Use the k-means algorithm to cluster the following one dimensional examples into 2 clusters: 2, 5, 10, 12, 3, 20, 31, 11, 24. Suppose that the initial seeds are 2 and 5. The convergence criterion is met when either there is no change between the clusters in two successive epochs or when the number of epochs has reached 5.

Show the final clusters. How many epochs were needed for convergence? There is no need to show your calculations.

Solution:
For simplicity let's sort the data first:
2 3 5 10 11 12 20 24 31
K1={2}, K2={5}

end of epoch 1:
K1={2, 3}, mean_K1=2.5
K2={5, 10, 11, 12, 20, 24, 31}, mean_K2=16.1
Stopping criterion not met

End of epoch 2:
K1={2, 3, 5}, mean_K1=3.3
K2={10, 11, 12, 20, 24, 31}, mean_K2=18
Stopping criterion not met

End of epoch 3:
K1={2, 3, 5, 10}, mean_K1=5
K2={11, 12, 20, 24, 31}, mean_K2=19.6
Stopping criterion not met

End of epoch 4:
K1={2, 3, 5, 10, 11,12}, mean_K1=7.2
K2={20, 24, 31}, mean_K2=25
Stopping criterion not met

End of epoch 5:

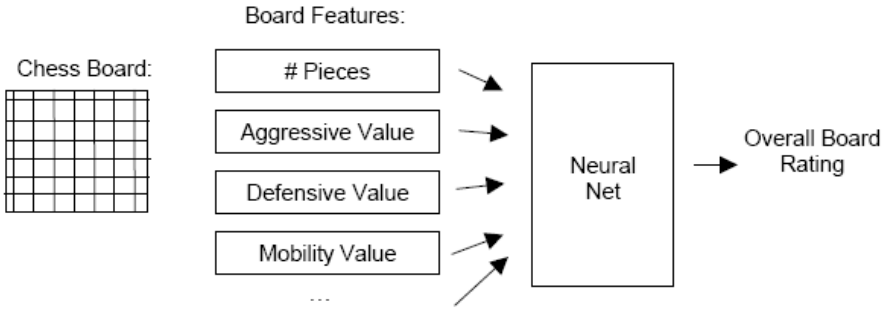
K1={2, 3, 5, 10, 11,12}, mean_K1=7.2
K2={20, 24, 31}, mean_K2=25
Stopping criterion is met – no change in clusters

Note: The question asks you only to show the final clusters and number of epochs, so the answer is:

Clusters: K1={2, 3, 5, 10, 11,12}, K2={20, 24, 31}
5 epochs were needed.

Question 8. You task is to develop a computer program to rate chess board positions. You got an expert chess player to rate 100 different chessboards and then use this data to train a backpropagation neural network, using board features as the ones shown in the figure below.

Select the correct answer ("Yes" or "No") in the questions below. Select "Yes" for all issues that could, in principle, limit your ability to develop the best possible chess program using this method. Select "No" for all issues that could not.



a) The backpropagation network may be susceptible to overfitting of the training data, since you tested its performance on the training data instead of using cross validation.

b) The backpropagation neural network can only distinguish between boards that are completely good or completely bad.

c) The backpropagation network implements gradient descent, so it may converge to a set of weights that is only a local minimum rather than the global minimum.

d) You should have used higher learning rate and momentum to guarantee convergence to the global minimum.

e) The topology of your neural net might not be adequate to capture the expertise of the human expert.

Answers:

a) Yes

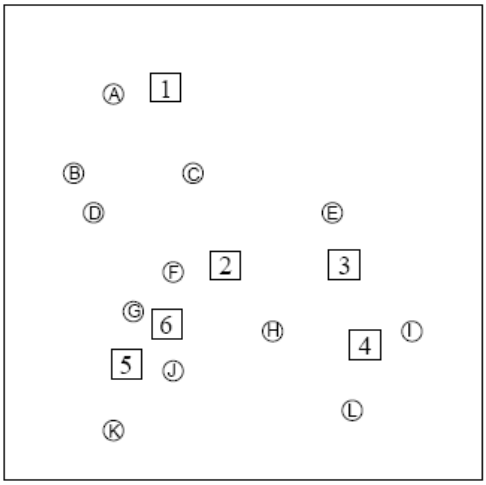
b) No. Backpropagation neural networks can be applied for both classification and regression tasks.

c) Yes

d) No

e) Yes. Too few neurons – underfitting; too many – overfitting.

Question 9. In the figure below, the circles are training examples and the squares are test examples, i.e. we are using the circles to predict the squares. Two algorithms are used: 1-Nearest Neighbour and 3-Nearest Neighbour.



We are given the following results about the squares:

Square	Using 1-Nearest Neighbors	Using 3-Nearest Neighbors
1	-	+
2	-	
3		+
4	+	-
5		-

What will be the class of the following examples? Write +, - or U for cannot be determined.

1) Circle L:
2) Circle I:
3) Circle H:
4) Circle E:
5) Circle K:
6) Circle C:
7) Square 6 using 1-Nearest Neighbour:
8) Square 6 using 3-Nearest Neighbour:
9) Square 3 using 1-Nearest Neighbour?
10) Square 5 using 1-Nearest Neighbour?

Answer:
Circle L: -

Circle I: +
Circle H: -
Circle E: +
Circle K: U
Circle C: +
Square 6 using 1-Nearest Neighbour: U
Square 6 using 3-Nearest Neighbour: -
Square 3 using 1-Nearest Neighbour: +
Square 5 using 1-Nearest Neighbour: U