Final Exam for UMU-54300 System och algoritmer för autonoma fordon, VT 2021

Name________________

Please note: Each multiple-choice question question is worth 1.5 pts, and has one and only one correct answer. If there is an option "All of the above", and all the above options are correct, then you should choose it instead of one of the correct options.

1. In the high-profile fatal accidents by Tesla and Uber vehicles in 2016 and 2018, which module in the processing pipeline was faulty and caused the accidents?

A. Perception
B. Planning
C. Control
D. System supervisor

ANS: ________________

A

2. True or False: the AUTOSAR Adaptive Platform is intended to replace the AUTOSAR Classic Platform in future Automotive E/E Architectures.

A. True
B. False

ANS: ________________

B

3. Which of the following V2X type is for communication with bicycle riders?

A. V2V
B. V2P
C. V2I
D. V2N

ANS: ________________

B

4. Consider a feedforward Fully-Connected Neural Network with 10 neurons in the (i-1)-th layer, and 100 neurons in the i-th layer. What is the number of parameters (weights and biases) at the i-th layer, i.e., the number of edges connecting the (i-1)-th layer with the i-th layer?

A. 1000
B. 1100

C. 110

D. 111

ANS: ________________

B

(Number of params at i-th layer is $(N_{i-1}+1)*N_i$, where N_i is the number of neurons at the i-th layer. So it is (10+1)*100=1100)

5. Consider a multi-class classification problem with 3 classes $(\text{cat}, \text{dog}, \text{horse})$. For a given input image of **cat**, the SoftMax-based classifier returns a vector of probabilities $(0.8, 0.1, 0.1)$ for each of the 3 classes. What is the Cross-Entropy Loss?

A. $-\log 0.8$

B. $-\log 0.1$

C. $\log 0.8$

D. $\log 0.1$

ANS: ________________

A

6. The Cross-Entropy Loss for multi-class classification problems is:

A. Always positive

B. Always negative

C. May be positive or negative

ANS: ________________

A

7. With “same padding” in CNN, with input spatial dimension W_1 x H_1, stride S=1, filter size 5 x 5, what is the pad size?

A. 1

B. 2

C. 3

D. 4

ANS: ________________

B

8. With “same padding” in CNN, with input spatial dimension W_1 x H_1, stride S=1, filter size 5 x 5, what is the output spatial dimension?

A. (W_1+1) x (H_1+1)

B. (W_1-1) x (H_1-1)

C. W_1 x H_1

D. None of the above

ANS: ________________

C

9. A two-stage object detector, e.g., Faster R-CNN), is typically less accurate but more efficient than a one-stage object detector, e.g., SSD.

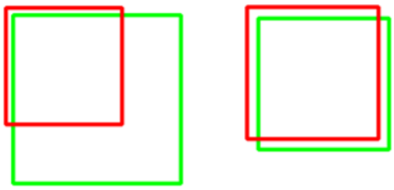
A. True

B. False

ANS: ________________

B

10. Consider the following object detection results, with the detected box shown in green and the ground-truth box shown in red. Which has a higher IOU (Intersection Over Union, IOU)?



A. The left one

B. The right one

ANS: ________________

B

11. Transposed Convolution can be used for:

A. Up-sampling, i.e., generate a larger image (in spatial dimension) from a smaller input image

B. Down-sampling, i.e., generate a smaller image (in spatial dimension) from a larger input image

C. Both

D. Neither

ANS: ________________

A

12. Which computer vision task requires the up-sampling operation?

A. Object detection

B. Segmentation

C. Classification

ANS: ________________

B

13. The Mean Average Precision (mAP) metric is used in:

A. Classification

B. Object detection

C. Segmentation

ANS: ________________

B

14. Consider a given point in a two-dimensional space (x_1, x_2)=(1,1), its L_2 distance to the origin (0, 0), $\|(x_1, x_2)\|_2$ is_____; its L_∞ distance to the origin $\|(x_1, x_2)\|_\infty$ is_____.

A. 1.0, $\sqrt{2}$

B. $\sqrt{2}$, 1.0

C. 1.0, 1.0

D. $\sqrt{2}$, $\sqrt{2}$

ANS: ________________

B

15. Consider a given point in a two-dimensional space (x_1, x_2)=(1,1), it lies _____the L_2 norm ball $\|(x_1, x_2)\|_2 \leq 1$; it lies _____the L_∞ norm ball $\|(x_1, x_2)\|_\infty \leq 1$.

A. outside, outside

B. outside, inside

C. inside, outside

D. inside, inside

ANS: ________________

B

16. The Fast Gradient Sign Method (FGSM) for adversarial attacks:

A. takes one single large step in the gradient direction, followed by clipping to lie within the norm bound

B. takes many small steps in the gradient direction, followed by clipping to lie within the norm bound

C. All of the above

D. None of the above

ANS: ________________

A

17. A robust model obtained with Adversarial Training [Goodfellow et al., 2014] typically has a smoother loss surface than a non-robust model.

A. True

B. False

ANS: ________________

A

18. For which search algorithm is this true: at each node, expand all neighbor nodes at the present depth prior to moving on to the nodes at the next depth level.

A. Breadth-First Search (BFS)

B. Depth-First Search (DFS)

C. A* search

D. Dijkstra's algorithm

ANS: ________________

A.

19. Which may be an *admissible heurstic* $h(v)$ for A* search, if we use a weighted graph to represent the road network, the objective is to minimize total travel time from start to goal, and the edge cost is travel time between two locations?

A. The Manhattan distance to the goal.

B. The straight-line distance to the goal.

C. The straight-line distance to the goal divided by the maximum speed limit.

ANS: ________________

C.

20. Which module in the AD pipeline does Intel RSS (Responsibility-Sensitive Safety) address?

A. Perception.

B. Localization.

C. Planning.

D. Control.

ANS: ________________

C

21. Consider the RSS rule for Safe Longitudinal Distance

$$d_{min} = \left[v_r\rho + \frac{1}{2}\alpha_{max}\rho^2 + \frac{(v_r + \rho\alpha_{max})^2}{2\beta_{min}} - \frac{v_f^2}{2\beta_{max}}\right]_+$$

Assume response time ρ=0, max and min deceleration $\beta_{max} = \beta_{min} = 1\ m/s^2$, max acceleration $\alpha_{max} = 10$,:front vehicle speed $v_f = 0$ (it is parked), rear ego-vehicle speed $v_r = 10\ m/s$. What is d_{min}?

A. 100 m

B. 50 m

C. 10 m

D. None of the above

ANS: ________________

B

22. Which of the following are rules of RSS?

A. Do not hit the car in front (safe longitudinal distance).

B. Do not cut-in recklessly (safe lateral distance).

C. Right-of-Way is given, not taken.

D. Be careful in areas with limited visibility.

E. If the vehicle can avoid a crash without causing another one, it must.

F. All of the above.

G. None of the above

ANS: ________________

F

23. Which path planning algorithm(s) are guaranteed to find the optimal solution?

A. A* algorithm

B. Rapidly-exploring Random Tree (RRT)

C. Probabilistic Roadmap (PRM)

D. All of them

E. None of them

ANS: ________________

A

24. Newton's law $F = m \cdot a$ (force equals mass times inertia) is useful in

A. Vehicle kinematics

B. Vehicle dynamics

C. Both

D. Neither

ANS: ________________

B

25. In the Kinematic Bicycle Model, _____ is part of the control input, _____ is part of the system state

A. steering angle, vehicle heading angle

B. vehicle heading angle, steering angle

C. Both

D. Neither

ANS: ________________

A

26. Which of the following are true for Model-Predictive Control (MPC)?

A. Predictive control with lookahead

B. Handles constraints explicitly

C. Applicable to both linear and nonlinear systems

D. Model-based: requires the system model

E. All of the above

F. None of the above

ANS: ________________

E

27. Which of the following describes Classification and Regression in Supervised Learning?

A. Classification is for predict/classify discrete labels such as Male or Female, and Regression is used to predict continuous values such as price.

B. Regression is for predict/classify discrete labels such as Male or Female, and Classification is used to predict continuous values such as price.

C. Classification and Regression are both for predict/classify discrete labels such as Male or Female.

D. Classification and Regression are both used to predict continuous values such as price.

ANS: ________________

A

28. What are the characteristics of RL?

A. There is no supervisor, only a reward signal (may be sparse).

B. Feedback is delayed, not instantaneous.

C. Sequential data, not i.i.d. data.

D. All of the above

E. None of the above

ANS: ________________

D

29. Consider this Bellman Equation: $v_\pi(s) = \sum_a \pi(a|s) \sum_{r,s'} p(r, s'|s, a)\,[r + \gamma v_\pi(s')]$. In Model-Based RL, what does the "model" refer to?

A. $\pi(a|s)$

B. $p(r, s'|s, a)$

C. $v_\pi(s')$

ANS: ________________

B

30. What is this equation? $v_\pi(s) = \sum_a \pi(a|s) \sum_{r,s'} p(r, s'|s, a)\,[r + \gamma v_\pi(s')]$

A. Bellman Expectation Equation for State Value Function

B. Bellman Expectation Equation for Action Value Function

C. Bellman Optimality Equation for Optimal State Value Function

D. Bellman Optimality Equation for Optimal Action Value Function

ANS: ________________

A

31. For MDP planning, which is faster per sweep (cycle), but requires more sweeps?

ANS: ________________

A. Policy Iteration.

B. Value Iteration.

ANS: ________________

B

32. Which of the following(s) are on-policy learning algorithms?

A. Monte Carlo with Importance Sampling

B. Sarsa

C. Expected Sarsa

D. Q Learning

ANS: ________________

B

33. A smaller γ discount factor in an MDP implies the agent is:

A. near-sighted: agent cares about short-term rewards more than long-term rewards.

B. far-sighted: agent cares about long-term rewards more than short-term rewards.

ANS: ________________

A

34. What is the name of the function that map from (state, action) pair to the cumulative expected reward from it?

A. State value-function V(s)

B. Action value function Q(s,a)

C. Reward R

D. Return G_t

ANS: ________________

B

35. What is Bootstrapping?

A. making a prediction from another prediction as in TD, Sarsa and Q Learning

B. making a computer start faster

C. using cache-memory to get values faster, like putting a boot on quicker

D. solve a set of linear equations analytically

ANS: ________________

A

36. Which loss function is used in Semi-Gradient TD (0)?

A. Mean Absolute Error

B. Mean Squared Error

C. Huber loss

D. Sigmoid loss

ANS: ________________

B

37. Dyna-Q is a type of:

A. Model-based and Value-based RL

B. Model-based and Policy-based RL

C. Model-free and Value-based RL

D. Model-free and Policy-based RL

ANS: ________________

A

38. Which of the following relies on Importance Sampling for Off-Policy learning?

A. On-policy MC control

B. Off-policy MC Prediction

C. Q-Learning

D. Expected Sarsa

ANS: ________________

B

39. _____ learns online at every step, _____learns at the end of each episode when return for every state in the episode can be computed.

A. TD, MC

B. MC, TD

C. MC, Sarsa.

D. MC, Q Learning.

ANS: ________________

A

40. Expected Sarsa and Q Learning are:

A. Expected Sarsa is on-policy and QL is off-policy.

B. Expected Sarsa is off-policy and QL is on-policy.

C. Both are on-policy.

D. Both are off-policy.

ANS: ________________

D

41. (10 pts)

(a) Consider a medical diagnosis test with the following metrics among 20 participants: True Positive TP=9, False Negative FN=1, False Positive FP=1, True Negative TN=9. Calculate precision, recall, F1 score, accuracy, False Positive Rate (FPR). Show the formulas and calculation process.

ANS:

precision=$\frac{TP}{TP+FP}=\frac{9}{9+1}=0.9$, recall=$\frac{TP}{TP+FN}=\frac{9}{9+1}=0.9$, F1 score=$\frac{2*precision*recall}{precision+recall}=\frac{2*.9*.9}{.9+.9}=0.9$

accuracy=$\frac{TP+TN}{TP+FN+FP+TN}=\frac{9+9}{20}=0.9$, FPR=$\frac{FP}{FP+TN}=\frac{1}{1+9}=0.1$

(b) Repeat the calculation for TP=9, FN=1, FP=9, TN=1.

ANS:

precision=$\frac{TP}{TP+FP}=\frac{9}{9+9}=0.5$, recall=$\frac{TP}{TP+FN}=\frac{9}{9+1}=0.9$, F1 score=$\frac{2*precision*recall}{precision+recall}=\frac{2*.5*.9}{.5+.9}=0.64$

accuracy=$\frac{TP+TN}{TP+FN+FP+TN}=\frac{9+1}{20}=0.5$, FPR=$\frac{FP}{FP+TN}=\frac{9}{9+1}=0.9$

42. (10 pts)

(a) Convolutional Neural Networks I

Input volume: $56\times56\times64$ ($W_1=H_1=N_1=56, D_1=64$). 32 $1\times1\times64$ filters ($K=32, F=1$) w. stride $S=1$, no pad $P=0$. Show the formulas and calculation process.

1) Calculate the dimensions of the output volume, including spatial size and depth.
2) Calculate the total number of parameters, including weights and biases.

ANS:

Each activation map:

Spatial size: $\mathrm{W}_2=\mathrm{H}_2=\mathrm{N}_2=\frac{1}{S}(N_1+2P-F)+1=\frac{1}{1}(56-1)+1=56$

Depth: $D_2=K=32$

Output volume:$56\times56\times32$

No. params: each filter has $1*1*64+1=65$ params, so 32 filters add up to $65*32=2080$ params

(b) Repeat the calculation for: Input volume: $56\times56\times64$ ($W_1=H_1=N_1=56, D_1=64$). 32 $5\times5\times64$ filters ($K=32, F=1$) w. stride $S=1$, pad $P=2$.

ANS:

Each activation map:

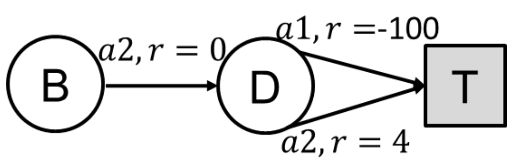
Spatial size: $\mathrm{W}_2=\mathrm{H}_2=\mathrm{N}_2=\frac{1}{S}(N_1+2P-F)+1=\frac{1}{1}(56+4-5)+1=56$

Depth: $D_2=K=32$

Output volume:$56\times56\times32$

No. params: each filter has $5*5*64+1=1601$ params, so 32 filters add up to $1601*32=51232$ params

43. (20 pts) Consider an episodic MDP w. deterministic env, 3 states $\{B,C,D\}$ and 2 actions $\{1,2\}$ at each state. Discount factor $\gamma=1$, learning rate $\alpha=1$. The initial state of each episode is B. Show the formulas and calculation process.



(a) (5 pts) Starting from a random policy, use Policy Iteration to derive the optimal policy.

ANS:

Bellman Exp Equation: $v_\pi(s) = \sum_a \pi(a|s) q_\pi(s,a)\,; q_\pi(s,a) = R_s^a + \gamma v_\pi(s')$

1st iteration:

Policy Evaluation:

- $v_\pi(B) = q_\pi(B, a2)$ (only one action choice)
- $q_\pi(B, a2) = 0 + v_\pi(D) = -48$ (in-place update)
- $v_\pi(D) = .5[q_\pi(D, a1) + q_\pi(D, a2)] = -48$
- $q_\pi(D, a1) = -100,\ q_\pi(D, a2) = 4$

Policy Improvement:

- $\pi'(B) = \text{argmax}_\text{a}\big(q_\pi(B, a2)\big) = a2$
- $\pi'(D) = \text{argmax}_\text{a}\big(q_\pi(D, a1), q_\pi(D, a2)\big) = a2$
- $q_\pi(C, a1) = -100, q_\pi(C, a2) = 4$

2nd iteration:

Policy Evaluation:

- $v_\pi(B) = q_\pi(B, a2)$
- $q_\pi(B, a2) = 0 + v_\pi(D) = 4$
- $v_\pi(D) = q_\pi(D, a2) = 4$
- $q_\pi(D, a2) = 4$

Policy Improvement:

- $\pi'(B) = \text{argmax}_\text{a}\big(q_\pi(B, a2)\big) = a2$
- $\pi'(D) = \text{argmax}_\text{a}\big(q_\pi(D, a1), q_\pi(D, a2)\big) = a2$
- $q_\pi(C, a1) = -100, q_\pi(C, a2) = 4$

	$V_\pi(B)$	$V_\pi(D)$
Init	0	0
Iter1	-48	-48
Iter2	4	4

Final optimal policy:

$\pi_*(B) = a2$

$\pi_*(D) = a2$

(b) (5 pts) Use Value Iteration to derive the optimal policy. Write out the set of equations and the final solution only. You do not need to show the iteration process.

Bellman Opt Equation: $v_*(s) = \max_a q_*(s,a); q_*(s,a) = R_s^a + \gamma v_*(s')$

- $v_*(B) = q_*(B, a2) = 4$
  - $q_*(B, a1) = 0 + v_*(D)$
- $v_*(D) = \max_a[q_*(D, a1),\ q_*(D, a2)] = 4$
  - $q_*(D, a1) = -100,\ q_*(D, a2) = 4$

- Value Iteration solution: $v_*(B) = 4,\ v_*(D) = 4$

	$V_*(B)$	$V_*(D)$
Init	0	0
Solution	4	4

Optimal policy: $\pi_*(\mathrm{B}) = \operatorname*{argmax}_{\mathrm{a}} q_*(B,a) = a2$; $\pi_*(\mathrm{D}) = \operatorname*{argmax}_{\mathrm{a}} q_*(D,a) = a2$

(c) (10 pts) Consider the following two episodes: EP1: (B,$a2$, 0, D,$a1$,−100, T); EP2: (B,$a2$, 0, D,$a2$,4, T). Perform Policy Evaluation with 1) Monte Carlo 2) TD learning 3) Sarsa 4) Q learning

MC:

MC update equation: $V(S_t) \leftarrow G_t$

EP1:

- $G(D) = -100 + V(T) = -100, G(B) = 0 + G(D) = -100$
- $V(B) = G(B) = -100,\ V(D) = G(D) = -100$

EP2:

- $G(D) = 4 + V(T) = 4, G(B) = 0 + G(D) = 4$
- $V(B) = G(B) = 4,\ V(D) = G(D) = 4$

	$V(B)$	$V(D)$
Init	0	0
EP1	-100	-100
EP2	4	4

TD:

TD update equation: $V(S_t) \leftarrow R_{t+1} + \gamma V(S_{t+1})$

EP1:

- $V(B) \leftarrow R_{t+1} + \gamma V(D) = 0 + 0 = 0$
- $V(D) \leftarrow R_{t+1} + \gamma V(T) = -100 + 0 = -100$

EP2:

- $V(B) \leftarrow R_{t+1} + \gamma V(D) = 0 - 100 = -100$
- $V(D) \leftarrow R_{t+1} + \gamma V(T) = 4 + 0 = 4$

	$V(B)$	$V(D)$
Init	0	0
Iter1	0	-100
Iter2	-100	4

Sarsa:

Sarsa update equation: $Q(S_t, A_t) \leftarrow R_{t+1} + \gamma Q(S_{t+1}, A_{t+1})$

EP1:

- $Q(B, a2) \leftarrow R_{t+1} + \gamma Q(D, a1) = 0 - 0 = 0$
- $Q(D, a1) \leftarrow R_{t+1} + \gamma Q(T, -) = -100 + 0 = -100$

EP2:

- $Q(B, a2) \leftarrow R_{t+1} + \gamma Q(D, a1) = 0 - 100 = -100$
- $Q(D, a2) \leftarrow R_{t+1} + \gamma Q(T, -) = 4 + 0 = 4$

	$Q(B, a_2)$	$Q(D, a_1)$	$Q(D, a_2)$
Init	0	0	0
Iter1	0	-100	0
Iter2	-100	-100	4

Q Learning:

QL update equation: $Q(S_t, A_t) \leftarrow R_{t+1} + \gamma \max_{a'} Q(S_{t+1}, a')$

EP1:

- $Q(B, a2) \leftarrow R_{t+1} + \gamma \max_{a} Q(D, a) = 0 + \max(0,\ 0)\ = 0$
- $Q(D, a1) \leftarrow R_{t+1} + \gamma Q(T, -) = -100 + 0 = -100$
- EP2:
- $Q(B, a2) \leftarrow R_{t+1} + \gamma \max_{a} Q(D, a) = 0 + \max(-100,\ 0)\ = 0$
- $Q(D, a1) \leftarrow R_{t+1} + \gamma Q(T, -) = 4 + 0 = 4$

	$Q(B, a_2)$	$Q(D, a_1)$	$Q(D, a_2)$
Init	0	0	0
Iter1	0	-100	0
Iter2	0	-100	4