

## i Front page

**Examination in TEK5040**

**2020 FALL**

**Duration: 16.12.2020, 09:00 to 13:30**

### **General information:**

- It is important that you check the course's semester page regularly. Important messages during the exam will be posted on the semester page. The messages during the exam can be posted in Canvas instead of the semester page if your course uses Canvas.
- Remember that your submission need to be anonymous, do not write your name in your submission.
- All examination support materials are permitted. You need to gather information from available sources, assess the information quality, and put it together in a submission based on your own processing of the content. The submission must reflect your individual level of knowledge
- The lecturers will give a digital "trøsterunde" via e-mail. Please see Canvas or the semester website for their contact information.
- Answers can be given in Norwegian or English. All questions should be answered. The questions are weighted differently. The maximum score is shown for each question.
- If a screenshot is small on your screen, try zooming:  
Press the keys ctrl and + at the same time  
or  
Press ctrl and scroll on the mouse wheel
- You have the opportunity to upload a file containing items such as diagrams and equations related to all your answers. This can be done under the last question called File Upload. Accepted file formats are PDF, PNG and JPEG. Further, make sure that the items in the file are clearly numbered according to the questions they are related to.

### **Collaboration**

- It is not permitted to communicate with other people about the exam and its questions during the exam. Plagiarism is not allowed. Do not directly copy text from lecture slides, books or other sources.
- You can be selected for a control interview on your examination answer, in order to determine your ownership of the answer. This discussion will not affect the grade, but can lead to the Department issuing a suspicion-of-cheating case.
- UiO's routines for handling suspicion of cheating can be found here: <https://www.uio.no/english/about/regulations/studies/studies-examinations/routines-cheating.html>

### **Contact:**

- [User support for exams](#)

**Good luck!**

## 1 Field of View

Assume you apply two convolutional layers consecutively to an input image  $x$ . Both convolutional layers have kernel size  $[5, 5]$  and stride 1 in both height and width dimension. We define the *field of view* of a neuron to be the pixels in the input image  $x$  that may affect the output of the neuron. The field of view for a neuron in the first convolutional layer forms a rectangle of size  $5 \times 5$ . What is the size of the (rectangular-shaped) field of view for a neuron in the second convolutional layer?

**Fill in your answer here**

Format ▾ | **B** *I* U  $x_2$   $x^2$  |  $I_x$  | | | | | |

Words: 0

Maximum marks: 12

## 2 Attending to Previous States

The amount of information a Recurrent Neural Network can remember is limited by the size of the state-vector, which may pose a problem for some applications where we need to keep track of a lot of information over time. One way to circumvent this problem is to let the Recurrent Neural Network *attend* to its previous state values. What can be some potential *disadvantages* of introducing this sort of attention?

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Maximum marks: 12

### 3 Proximal Policy Optimization

Improving *stability* and *sample efficiency* of reinforcement learning algorithms are important in making them more widely applicable. Briefly describe how the Proximal Policy Optimization (PPO) algorithm addresses these issues.

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## 4 Generative Adversarial Networks

Assume that you have a large collection of images of human faces. For each image you also know the *age* of the person depicted. Based on what you have learned in this course, describe a way you could use Generative Adversarial Networks (GANs) to create an application that takes three inputs

- image of a persons face
- current age of the depicted person
- desired output age of the person

and output a prediction of how the person might look at the desired output age. Hint: You may want to train different GANs on different subsets of the dataset.

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Maximum marks: 12

## 5 Learning Concepts

Meta-learning can be formulated as an optimization problem with the following objective function:

$$\theta^* = \arg \max_{\theta} \frac{1}{N} \sum_{n=1}^N \sum_{\mathbf{x}, \mathbf{y} \in \mathcal{D}_{query}^{(n)}} p_{\theta}(\mathbf{y} | \mathbf{x}, \mathcal{D}_{support}^{(n)})$$

where  $\mathcal{D}_{support}^{(n)}$  and  $\mathcal{D}_{query}^{(n)}$  are respectively the  $n^{\text{th}}$  support set and query set of the meta training set, whereas  $\mathbf{x}$  and  $\mathbf{y}$  are respectively the input and label of any data sample.  $p_{\theta}$  is a probability distribution parameterized by  $\theta$ . Describe a meta-learning technique which makes use of this objective function. Outline why the technique you described is indeed based on the above objective function.

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## 6(a) Bayesian Deep Learning

In variational inference, we try to approximate the posterior distribution  $p(\mathbf{w}|\mathcal{D})$  with a variational distribution  $q(\mathbf{w})$ , where  $\mathbf{w}$  and  $\mathcal{D}$  are network parameters and training data respectively. This is achieved by indirectly minimizing the KL divergence between the two distributions using a quantity known as Evidence Lower Bound (ELBO). The KL divergence and ELBO are respectively given by

$$\text{KL}(q(\mathbf{w})||p(\mathbf{w}|\mathcal{D})) = -\mathbb{E}_{q(\mathbf{w})} \ln \frac{p(\mathbf{w}|\mathcal{D})}{q(\mathbf{w})}$$

and

$$\text{ELBO} = -\mathbb{E}_{q(\mathbf{w})} \ln \frac{p(\mathbf{w}, \mathcal{D})}{q(\mathbf{w})},$$

where  $\mathbb{E}_{q(\mathbf{w})}$  is the expectation operation with respect to distribution  $q(\mathbf{w})$ .

Explain why ELBO is easier to work with than the KL divergence.

**Fill in your answer here**

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Maximum marks: 4

## 6(b) Bayesian Deep Learning

ELBO,  $\mathcal{L}(\lambda)$  can be written as

$$\text{ELBO} = \mathcal{L}(\lambda) = \mathbb{E}_{q(\mathbf{w}, \lambda)} [\ln p(\mathbf{w}, \mathcal{D}) - \ln q(\mathbf{w}, \lambda)]$$

where  $\lambda$  parameterizes the distribution  $q$ .

Paul approximates this with the following expression by sampling  $\mathbf{w}^s$  from  $q(\mathbf{w}, \lambda)$ .

$$\hat{\mathcal{L}}(\lambda) = \frac{1}{S} \sum_{s=1}^S [\ln p(\mathbf{w}^s, \mathcal{D}) - \ln q(\mathbf{w}^s, \lambda)],$$

where  $S$  is the number of samples used.

He intends to find the gradient of  $\hat{\mathcal{L}}(\lambda)$  and hence optimize it with respect to  $\lambda$ . Briefly explain why Paul would not succeed. Give a short outline of a more successful procedure Paul could have used instead.

**Fill in your answer here**

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Maximum marks: 8



## 7 Deep Learning for Control

Following are some challenges in application of deep learning for controlling mobile robots.

- Compounding errors
- Complex reward functions
- High risk in exploration in unknown environments

Briefly discuss approaches suitable for addressing these challenges and what limitations these approaches themselves have.

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Maximum marks: 12

## 8(a) 3D Processing

Despite the fact that 3D inputs and 3D filters are used in regular convolution (for example those used in popular convolution networks such as ResNet), such convolution operations are not considered 3D convolutions. Explain the difference between those convolution operations and 3D convolutions.

**Fill in your answer here**

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Words: 0

Maximum marks: 3

**8(b) 3D Processing**

A student is given a set of point clouds and each point cloud in the set consists of 100 three-dimensional points. Any given point cloud represents one of 5 different object classes. The student is asked to design a network to classify any given point cloud into one of the 5 object classes. He designs a Multi-layer Perceptron (MLP) which takes an input of dimension 3 and gives out a vector of dimension 256. For any given point cloud from the set, this MLP operates in parallel over every point in the point cloud.

What are the dimensions of the MLP outputs for the whole point cloud?

**Fill in your answer here**

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Words: 0


Maximum marks: 3

**8(c) 3D Processing**

If the student wants the network to have permutation invariance, how can he combine the MLP outputs?

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Maximum marks: 3


**8(d) 3D Processing**

How the student can improve the robustness of the network against geometric transformations of the inputs?

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## 8(e) 3D Processing

The student pays his attention to a 3D object tracking task where the goal is to track a slowly moving object in the 3D space using a series of point clouds. There are no requirements on speed or memory consumption. He plans to extend a Siamese fully convolutional network based approach for handling this case. Propose a 3D processing network architecture suitable for this task.

**Fill in your answer here**

Format

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




























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Words: 0

Maximum marks: 4

## 9 File Upload

Here you can upload a PDF, PNG or JPEG file which contains items such as diagrams and equations etc. related to your answers in the previous questions. Remember to mark every item in the file with the relevant question number.



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Maximum marks: 0