i Front page

Written home exam in TEK5040/9040 2021 Fall

Duration: 13.12.2021, 09:00 to 13.12.2021, 13:30

It is important that you read this cover page carefully before you start. General information:

- Important messages during the exam are given directly from the course teacher on the course's semester page or in Canvas (if used in your course). It is therefore important that you check the course's semester page / Canvas room regularly.
- Your answer should reflect your own independent work and should be a result of your own learning and work effort.
- All sources of information are allowed for written home exams. If you reproduce a text from books, online articles, etc., a reference to these sources must be provided to avoid suspicions of plagiarism. This also applies if a text is translated from other languages.
- You are responsible for ensuring that your exam answers are not available to others during the exam period, neither physically nor digitally.
- Remember that your exam answers must be anonymous; do not state either your name or that of fellow students.
- If you want to withdraw from the exam, press the hamburger menu at the top right of Inspera and select "Withdraw".

Collaboration during the exam:

It is not allowed to collaborate or communicate with others during the exam. Cooperation and communication will be considered as attempted cheating. A plagiarism control is performed on all submitted exams where text similarities between answers are checked. If you use notes that have been prepared in collaboration with others before the exam, this might be detected in a plagiarism control. Textual similarities such as these can be considered by graders as a show of low independence or even attempted cheating. Refrain from copying/pasting from notes made in collaboration with others.

Use of sources: [can be removed]

The answer must be written with an academic standard. Read UiO's website <u>Use of sources and citations</u>

Cheats:

Read about what is considered cheating on UiO's website.

Digital hand drawing / file upload: [the course teacher removes this section if the exam does not have digital hand drawings]

You have been given 30 min. extra time for uploading files (e.g. digital hand drawings). <u>Check out how to submit digital hand drawings</u>

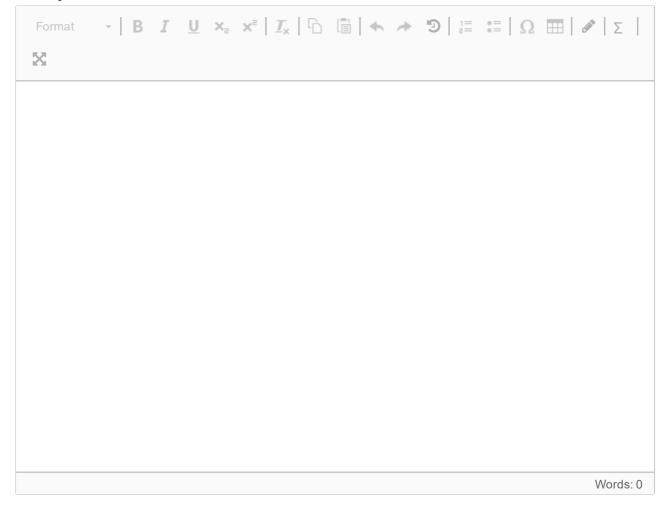
Contact information: User support exam

¹ Field of View

Assume that you apply two convolutional layers consecutively to an input image x. The first convolutional layer has a kernel size [5,5] and stride 1 in both height and width dimension. The second convolutional layer has a kernel size of [3,3] with stride 2 in both height and width dimensions. 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 5×5 .

What is the size of the (rectangular-shaped) field of view for a neuron in the second convolutional layer?

Fill in your answer here



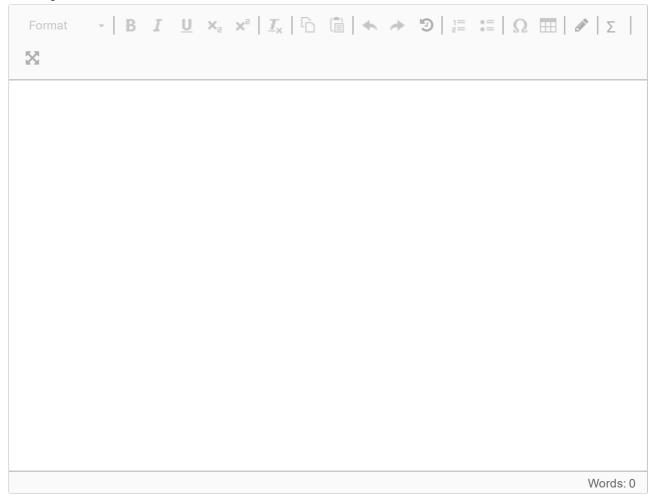
² Self-Attention

Self-attention based networks are an alternative to Recurrent Neural Networks (RNNs) in sequence modelling.

Briefly describe one disadvantage and one advantage of self-attention networks compared to RNNs.

How can you remedy the disadvantage you described?

Fill in your answer here



³ Policy gradients

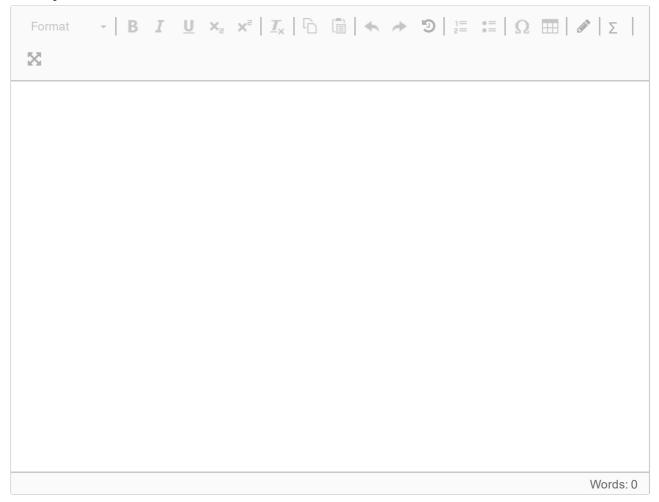
In policy gradient based reinforcement learning, we try to maximize the expected reward $J(\theta) = E_{\tau \sim \theta}[R(\tau)]$, where $\tau \sim \theta$ means that the trajectory τ is sampled with a policy π_{θ} parameterized by θ and $R(\tau)$ is the reward associated with a trajectory τ . It can be shown that $\nabla_{\theta}J(\theta) = E_{\tau \sim \theta}[\nabla_{\theta}\log P(\tau|\theta)R(\tau)]$ where $P(\tau|\theta)$ is the probability of a trajectory τ under the policy π_{θ} .

We can instead maximize the importance sampling based estimation of the expected reward $U(\theta) = E_{\tau \sim \theta_{old}} [\frac{P(\tau|\theta)}{P(\tau|\theta_{old})} R(\tau)]$ where θ_{old} is the previous parameter vector of the policy.

Name a reinforcement learning algorithm based on this fomulation.

Differentiate $U(\theta)$ with respect to θ and show that $\nabla_{\theta}J(\theta)=\nabla_{\theta}U(\theta)$ evaluated at $\theta=\theta_{old}$.

Fill in your answer here



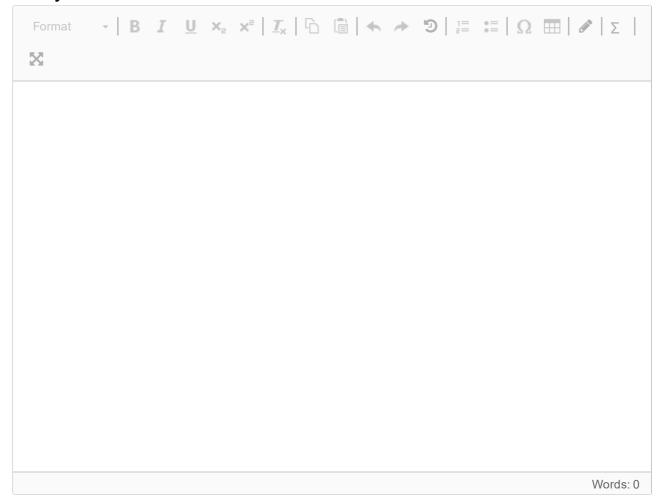
⁴ Generative Adverserial Networks

Assume that there are two datasets, one consisting of sonar images and the other consisting of optical images. The images of both datasets depict the seafloor, but it is hard to find a sonar image and an optical image of the same location. A student wants to train a generative adversarial network (GAN) to transform a given sonar image of a particular location to an optical image showing the same location. He tries to apply a conditional GAN for this problem.

Why is it unlikely that the student would succeed?

Briefly describe the essential steps of a better approach to solve this problem.

Fill in your answer here



^{5(a)} Meta-learning

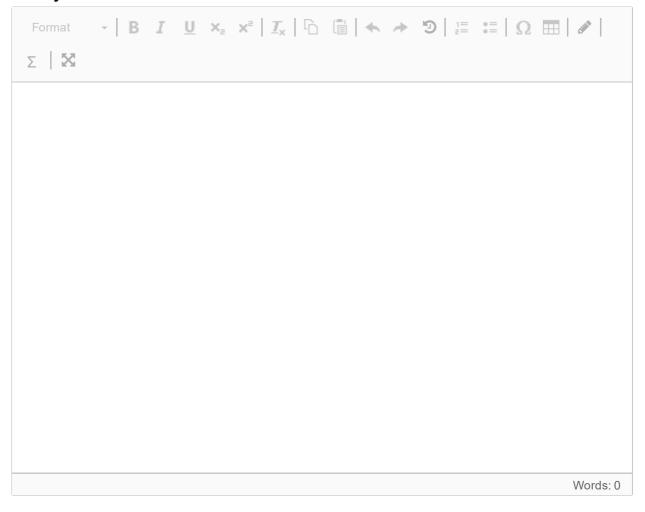
Meta-learning can be formulated as an optimization problem with the following objective function:

$$heta^\star = rg \max_ heta rac{1}{N} \sum_{n=1}^N \sum_{\mathbf{x}, \mathbf{y} \in \mathcal{D}_{query}^{(n)}} p_ heta(\mathbf{y}|\mathbf{x}, \mathcal{D}_{support}^{(n)})$$

where $\mathcal{D}^{(n)}_{support}$ and $\mathcal{D}^{(n)}_{query}$ are respectively the n^{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_{θ} is a probability distribution parameterized by θ .

Outline why meta-learning with Siamese networks is based on the above objective function. (Hint: Identify how the support set and the query set are used in meta-training of Siamese networks.)

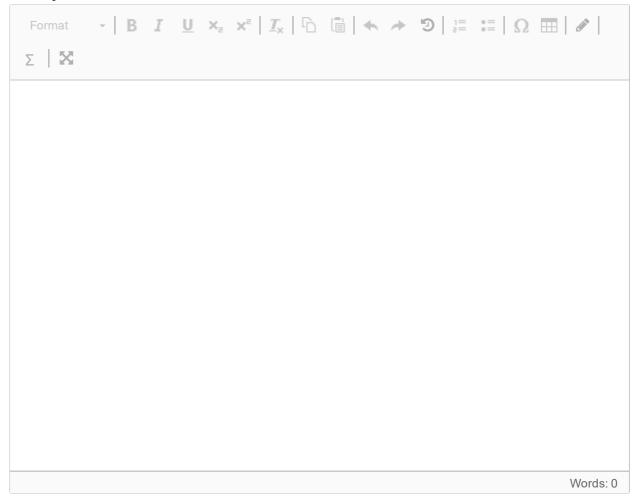
Fill in your answer here



^{5(b)} Self-supervised learning

Briefly describe the role of the pretext task and the downstream task in self-supervised learning.

Fill in your answer here



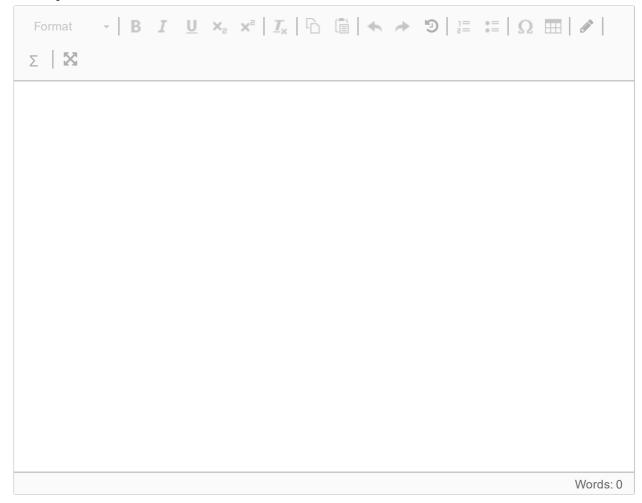
^{6(a)} Bayesian Deep Learning

Let \boldsymbol{X} and \boldsymbol{Y} respectively be a sequence of input vectors and the corresponding outputs of a neural network parameterized by \boldsymbol{w} . In Bayesian deep learning we try to estimate the posterior distribution $p(\boldsymbol{w}|\boldsymbol{X},\boldsymbol{Y})$.

Write the Bayes formula which expresses the posterior distribution in terms of the prior distribution $p(\boldsymbol{w})$ and the likelihood distribution $p(\boldsymbol{Y}|\boldsymbol{X},\boldsymbol{w})$.

Explain why it is difficult to perform exact Bayesian inference in practical deep learning.

Fill in your answer here



6(b) Evidence Lower Bound

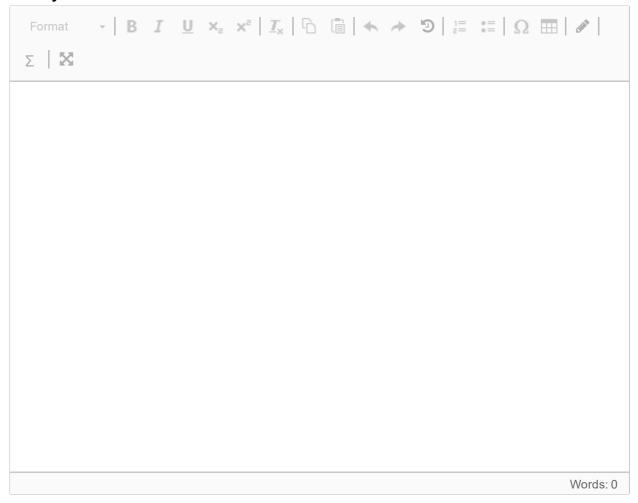
In variational inference, we try to approximate the posterior distribution $p(\boldsymbol{w}|\boldsymbol{X},\boldsymbol{Y}) = p(\boldsymbol{w}|\mathcal{D})$ with a variational distribution $q(\boldsymbol{w},\lambda)$. Here $\mathcal{D}=(\boldsymbol{X},\boldsymbol{Y})$ is training data and λ is the parameter vector of the variational distribution $q(\boldsymbol{w},\lambda)$.

This approximation is done through the optimization of a quantity called Evidence Lower Bound (ELBO), $\mathcal{L}(\lambda)$ which can be written as

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

Describe the essential steps of a procedure for sample based estimation of the gradients of ELBO $\nabla_{\lambda}\mathcal{L}(\lambda)$

Fill in your answer here

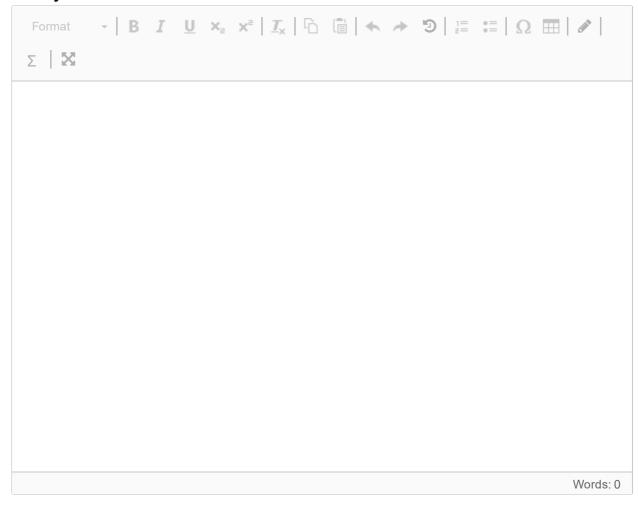


^{7(a)} Inverse Reinforcement Learning

Inverse Reinforcement Learning (IRL) has been proposed as a solution for the problem of manual design of complex reward functions.

Name two challenges in IRL.

Fill in your answer here



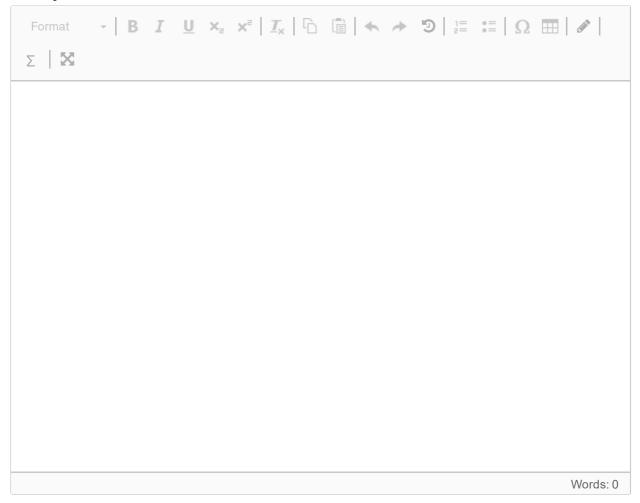
^{7(b)} Generative Adversarial Imitation Learning

There is an equivalence between Generative Adversarial Networks (GAN) and Generative Adversarial Imitation Learning (GAIL).

Write down the entities/operations in GAIL which are equivalent to the following entities/operations in GAN:

- Generator (G)
- Discriminator (D)
- Real data samples x^{real}
- ullet Fake data samples x^{fake}
- G maximizes the probability of x^{fake}
- ullet D maximizes the probability of x^{real}
- ullet D minimizes the probability of x^{fake}

Fill in your answer here

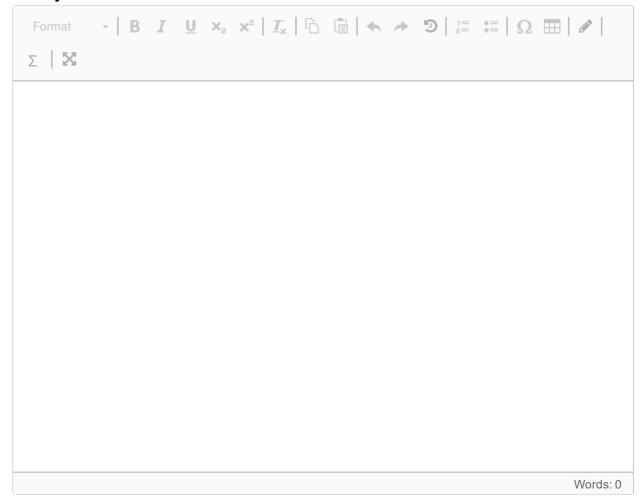


8(a) 3D Processing

A student is given a set of point clouds and each point cloud in the set consists of 100 three-dimensional points. The student is asked to design a network to perform segmentation on any given point cloud from the set. He designs a graph neural network based on a series of graph convolution layers.

How many nodes are likely to be there in the graph of any given layer?

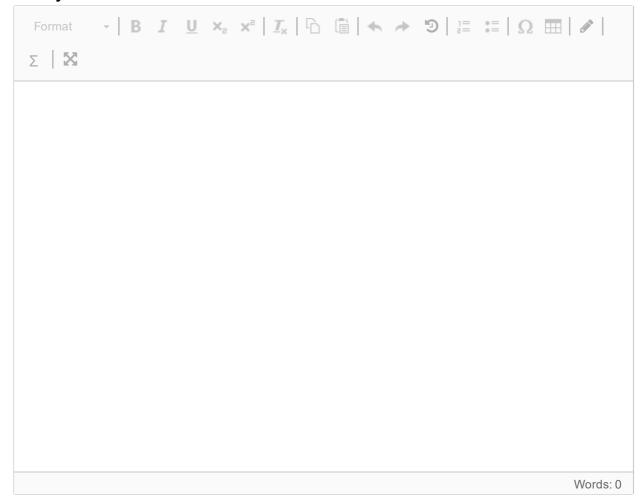
Fill in your answer here



8(b) 3D Processing

Another student tries to solve the same problem by employing a layer which consists of a series of identical Multi-layer Perceptrons (MLPs) independently operating on the input points. Compared to the graph convolution based system, what disadvantages does this approach have?

Fill in your answer here



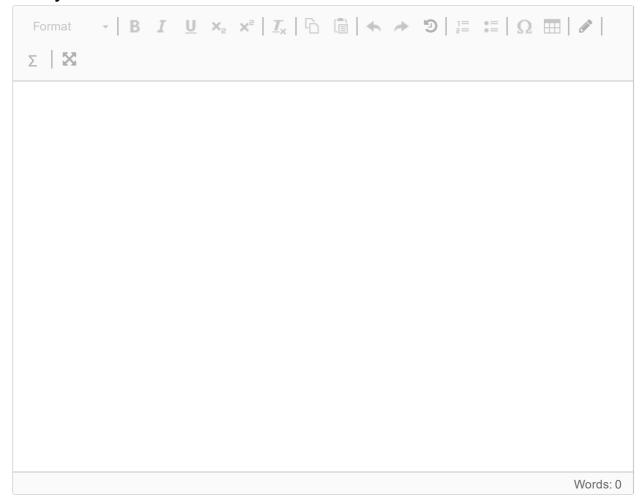
8(c) Multi-object tracking

Graph neural networks can be used in multi-object tracking to solve the association problem. Let us assume that tracking is performed on three frames at time steps t=1,2,3. There are 3, 3 and 4 detections respectively at t=1,2,3.

Draw a graph to represent the possible associations.

Describe briefly how to calculate initial node and edge features, and give an outline of a suitable procedure to solve the association problem.

Fill in your answer here

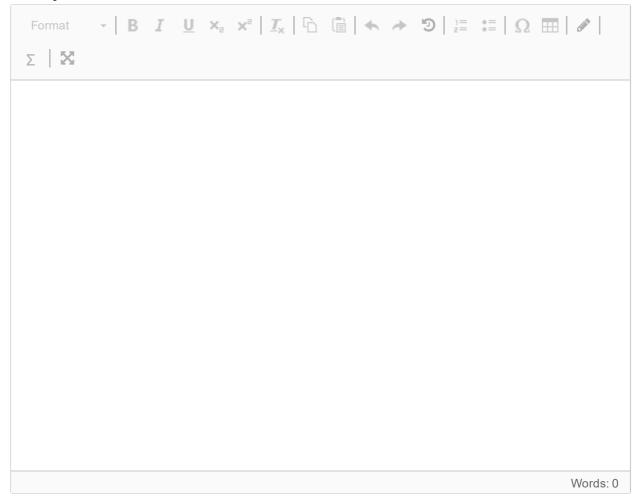


8(d) Single object tracking

For single object tracking, a Siamese neural network can be used.

Explain why the network should be fully convolutional in order for the technique to work correctly.

Fill in your answer here



⁹ Kopi av 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.

