Chair of Visual Computing & Artificial Intelligence
Department of Informatics
Technical University of Munich

Esolution
Place student sticker here

Note:

- During the attendance check a sticker containing a unique code will be put on this exam.
- This code contains a unique number that associates this exam with your registration number.
- This number is printed both next to the code and to the signature field in the attendance check list.

Introduction to Deep Learning

Exam: IN2346 / Endterm
Examiner: Prof. Leal-Taixé and Prof. Nießner
Date: Tuesday 11th August, 2020
Time: 08:00 – 09:30

	P 1	P 2	P 3	P 4	P 5	P 6	P 7	P 8
I								

Left room from ______________ to ______________

from ______________ to ______________

Early submission at ______________

Notes ____

Endterm

Introduction to Deep Learning

Prof. Leal-Taixé and Prof. Nießner
Chair of Visual Computing & Artificial Intelligence
Department of Informatics
Technical University of Munich

Tuesday 11th August, 2020
08:00 – 09:30

Working instructions

- This exam consists of **20 pages** with a total of **8 problems**.
  Please make sure now that you received a complete copy of the exam.
- The total amount of achievable credits in this exam is 90 credits.
- Detaching pages from the exam is prohibited.
- Allowed resources: **none**
- Do not write with red or green colors nor use pencils.
- Physically turn off all electronic devices, put them into your bag and close the bag.
- If you need additional space for a question, use the additional pages in the back and properly note that you are using additional space in the question's solution box.

Problem 1 **Multiple Choice Questions: (18 credits)**

- For all multiple choice questions any number of answers, i.e. either zero (!), one, all or multiple answers can be correct.
- For each question, you'll receive 2 points if all boxes are answered correctly (i.e. correct answers are checked, wrong answers are not checked) and 0 otherwise.

How to Check a Box:

- Please **cross** the respective box: ☒ (interpreted as **checked**)
- If you change your mind, please **fill** the box: ■ (interpreted as **not checked**)
- If you change your mind again, please place a cross to the left side of the box: ✗ ■ (interpreted as **checked**)

a) Which of the following statements regarding successful ImageNet-classification architectures are correct?

- ☐ VGG16 uses Skip Connections
- ☐ AlexNet uses filters of different kernel sizes.
- ☐ InceptionV3 uses filters of different kernel sizes.
- ☐ VGG16 only uses convolutional layers.

b) You train a neural network and the train loss diverges. What are reasonable things to do? (check all that apply)

- ☐ Decrease the learning rate.
- ☐ Add dropout.
- ☐ Increase the learning rate.
- ☐ Try a different optimizer.

c) What is the correct order of operations for an optimization with gradient descent?

(a) Update the network weights to minimize the loss.

(b) Calculate the difference between the predicted and target value.

(c) Iteratively repeat the procedure until convergence.

(d) Compute a forward pass.

(e) Initialize the neural network weights.

- ☐ bcdea
- ☐ ebadc
- ☐ eadbc
- ☐ edbac

d) Consider a simple convolutional neural network with a single convolutional layer. Which of the following statements is true about this network?

- ☐ It is rotation invariant.
- ☐ It is translation equivariant.
- ☐ All input nodes are connected to all output nodes.
- ☐ It is scale-invariant.

e) Which of the following activation functions can lead to vanishing gradients?

- ☐ Tanh.
- ☐ ReLU.
- ☐ Sigmoid.
- ☐ Leaky Relu.

f) Logistic regression (check all that apply).

- ☐ Is a linear function.
- ☐ Is a supervised learning algorithm.
- ☐ Uses a type of cross-entropy loss.
- ☐ Allows to perform binary classification.

g) A sigmoid layer

- ☐ cannot be used during backpropagation.
- ☐ has a learnable parameter.
- ☐ maps surjectively to values in (-1, 1), i.e., hits all values in that interval.
- ☐ is continuous and differentiable everywhere.

h) Your training loss does not decrease. What could be wrong?

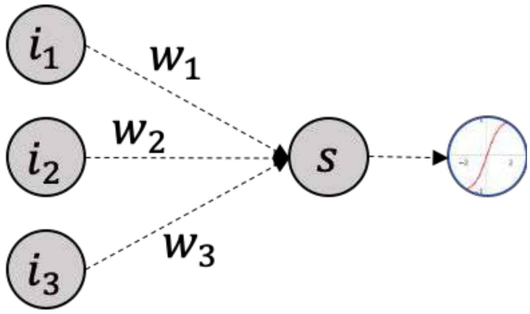
- ☐ Learning rate is too high.
- ☐ Too much regularization.
- ☐ Dropout probability not high enough.
- ☐ Bad initialization.

i) Which of the following have trainable parameters? (check all that apply)

- ☐ Leaky ReLU
- ☐ Batch normalization
- ☐ Dropout
- ☐ Max pooling

Problem 2 Activation Functions and Weight Initialization (8 credits)

For your first job, you have to set up a neural network but you have some issue with its weight initialization. You remember from your I2DL lecture that you can sample the weights from a zero-centered normal distribution, but you can't remember which variance to use. Therefore, you set up a small network and try some numbers. You initialize the weights one time with $\text{Var}(\mathbf{w}) = 0.02$ and one time with $\text{Var}(\mathbf{w}) = 1.0$:



Inputs:

- $i_1 = 2, i_2 = -4, i_3 = 1$

$\text{Var}(\mathbf{w}) = 0.02$:

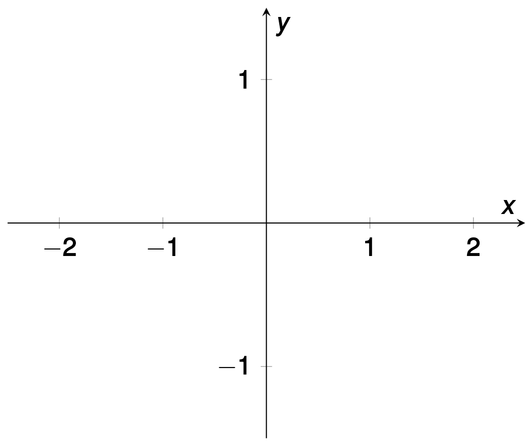
- $w_1 = 0.05, w_2 = 0.025, w_3 = -0.03$

$\text{Var}(\mathbf{w}) = 1.0$:

- $w_1 = 1.0, w_2 = 0.5, w_3 = 1.5$

0 1 2

a) Compute a forward pass for each set of weights and draw the results of the linear layer in the Figure of the tanh plot. You don't need to compute the tanh.



b) Using the results above, explain what problems can arise during backpropagation of deep neural networks when initializing the weights with too small and too large variance. Also, explain the root of these problems.

0
1
2

c) Which initialization scheme did you learn in the lecture that tackles these problems? What does this initialization try to achieve in the activations of deep layers of the neural network?

0
1
2

d) After switching from tanh to ReLU activation functions, one of your initial problems occurs again. Why does this happen? How can you modify the initialization scheme proposed in c) to adjust it for this new non-linearity?

0
1
2

Problem 3 Batch Normalization and Computation Graphs (6 credits)

For an input vector **x** as well as variables γ and β the general formula of batch normalization is given by

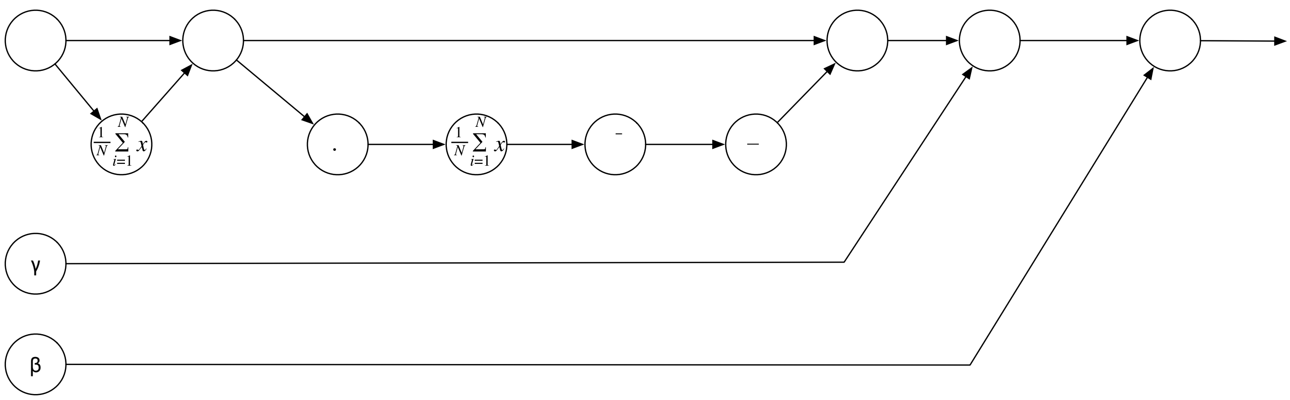
$$\hat{\mathbf{x}} = \frac{\mathbf{x} - \mathrm{E}[\mathbf{x}]}{\sqrt{Var[\mathbf{x}]}}$$
$$\mathbf{y} = \gamma\hat{\mathbf{x}} + \beta.$$

a) Why would one want to apply batch normalization in a neural network?

b) Why are γ and β needed in the batch normalization formula?

c) How is a batch normalization layer applied at training (1p) and at test (1p) time?

d) Computational graph of a batch normalization layer. Fill out the nodes (circles) of the following computational graph. Each node can consist of one of the following operations $+,\ -,\ *,\ ^2,\ \sqrt{\ },\ \frac{1}{\cdot}$.



Problem 4 Convolutional Neural Networks and Receptive Field (12 credits)

A friend of yours asked for a quick review of convolutional neural networks. As he has some background in computer graphics, you start by explaining previous uses of convolutional layers.

a) You are given a two dimensional input (e.g., a grayscale image). Consider the following convolutional kernels

0 1 2

$$C_1 = \frac{1}{9} \cdot \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}, \qquad C_2 = \begin{pmatrix} 1 & -1 \\ 1 & -1 \end{pmatrix}.$$

What are the effects of the filter kernels C_1 and C_2 when applied to the image?

After showing him some results of a trained network, he immediately wants to use them and starts building a model in Pytorch. However, he is unsure about the layer sizes so you quickly help him out.

b) Given a Convolution Layer in a network with 5 filters, filter size of 7, a stride of 3, and a padding of 1. For an input feature map of $26 \times 26 \times 26$, what is the output dimensionality after applying the Convolution Layer to the input?

0 1 2

c) You are given a convolutional layer with 4 filters, kernel size 5, stride 1, and no padding that operates on an RGB image.

0 1 2

1. What is the shape of its weight tensor?
2. Name all dimensions of your weight tensor.

Now that he knows how to combine convolutional layers, he wonders how deep his network should be. After some thinking, you illustrate the concept of receptive field to him by these two examples. For the following two questions, consider a grayscale 224x224 image as network input.

d) A convolutional neural network consists of 3 consecutive 3×3 convolutional layers with stride 1 and no padding. How large is the receptive field of a feature in the last layer of this network?

0 1

0 1 2

e) Consider a network consisting of a single layer.

1. What layer choice has a receptive field of 1?
2. What layer has a receptive field of the full image input?

Blindly, he stacks 10 convolutional layers together to solve his task. However, the gradients seem to vanish and he can't seem to be able to train the network. You remember from your lecture that ResNet blocks were designed for these purposes.

0 1 2

f) Draw a ResNet block in the image above (1p) containing two linear layers, which you can represent by l_1 and l_2. For simplicity, you don't need to draw any non-linearities. Why does such a block improve the vanishing gradient problem in deep neural networks (1p)?

0 1

g) For your above drawing, given the partial derivative of the residual block $R(x) = l_2(l_1(x))$ as $\frac{\partial R(x)}{\partial x} = r$, calculate $\frac{\partial H(x)}{\partial x}$.

Problem 5 Training a Neural Network (15 credits)

A team of architects approaches you for your deep learning expertise. They have collected nearly 5,000 hand-labeled RGB images and want to build a model to classify the buildings into their different architectural styles. Now they want to classify images of architectures into 3 classes depending on their style:

Islamic

Baroque

Soochow

a) How would you split your dataset and give a meaningful percentage as answer.

b) After visually inspecting the different splits in the dataset, you realize that the training set only contains pictures taken during the day, whereas the validation set only has pictures taken at night. Explain what is the issue and how you would correct it.

c) As you train your model, you realize that you do not have enough data. Unfortunately, the architects are unable to collect more data so you have to temper the data. Provide 4 data augmentation techniques that can be used to overcome the shortage of data.

0
1

What is the saddle point and what is the problem with GD?

0
1

e) While training your classifier you experience that loss only slowly converges and always plateaus independent of the used learning rate. Now you want to use Stochastic Grading Descent (SGD) instead of Gradient Descent (GD). What is an advantage of SGD compared to GD in dealing with saddle points?

0
1

f) Explain the concept behind momentum in SGD

0
1

g) Why would one want to use larger mini-batches in SGD?

0
1

h) Why do we usually use small mini-batches in practice?

0
1

i) There exists a whole zoo of different optimizers. Name an optimizer that uses both first and second order moment

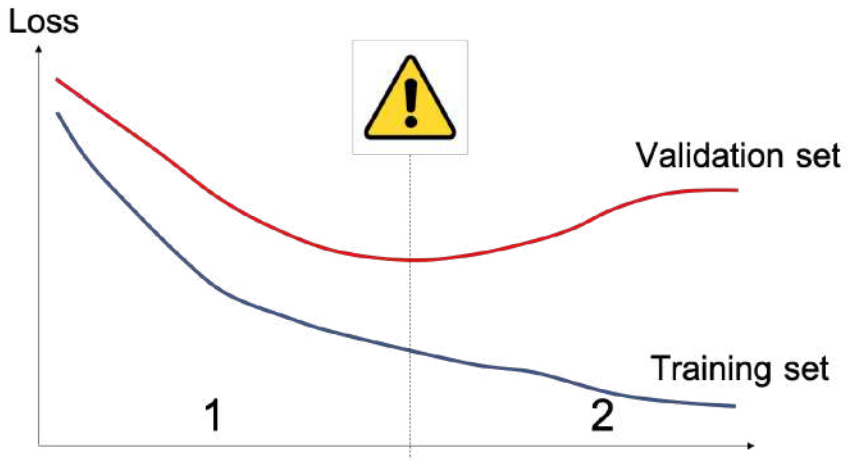
0
1
2

j) Choosing a reasonable learning rate is not easy.

1. Name a problem that will result from using a learning rate that is too high (1p).
2. Name a problem that will arise from using a learning rate that is too low (1p)?

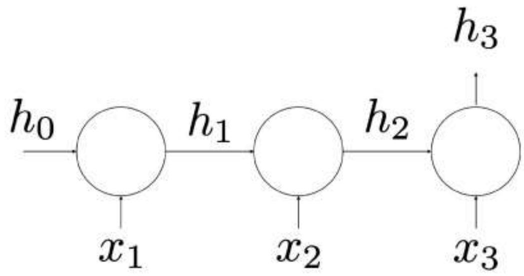
k) Finally you plot the loss curves with a suitable learning rate for both training data and validation data. What's the issue of period 2 called? Name a possible actions that you could do without changing the number of parameters in your network to counteract this problem.

0
1
2



Problem 6 **Recurrent Neural Networks and Backpropagation (9 credits)**

Consider a vanilla RNN cell of the form $h_t = \tanh(V \cdot h_{t-1} + W \cdot x_t + b)$. The figure below shows the input sequence x_1, x_2, and x_3.



a) Given the dimensions $x_t \in \mathbb{R}^3$ and $h_t \in \mathbb{R}^5$, what is the number of parameters in the RNN cell? (Calculate final number)

b) If x_t and b are the 0 vector, then $h_t = h_{t-1}$ for any value of h_t. Discuss whether this statement is correct.

Now consider the following **one-dimensional** ReLU-RNN cell without bias b.

$$h_t = \mathrm{ReLU}(V \cdot h_{t-1} + W \cdot x_t)$$

(Hidden state, input, and weights are scalars)

c) Calculate h_2 and h_3 where

$$V = -3, \quad W = 3, \quad h_0 = 0, \quad x_1 = 2, \quad x_2 = 3 \quad \text{and } x_3 = 1.$$

d) Calculate the derivatives $\frac{\partial h_3}{\partial V}$, $\frac{\partial h_3}{\partial W}$, and $\frac{\partial h_3}{\partial x_1}$ for the forward pass of the ReLU-RNN where

$$V = -2, \quad W = 1, \quad h_0 = 2, \quad x_1 = 2, \quad x_2 = \frac{3}{2} \quad \text{and } x_3 = 4.$$

for the forward outputs

$$h_1 = 0, \quad h_2 = \frac{2}{3}, \quad h_3 = 1.$$

Use that $\frac{\partial}{\partial x}\text{ReLU}(x)\Big|_{x=0} = 0$.

0 1 2 3

0
1
2

e) A Long-Short Term Memory (LSTM) unit is defined as

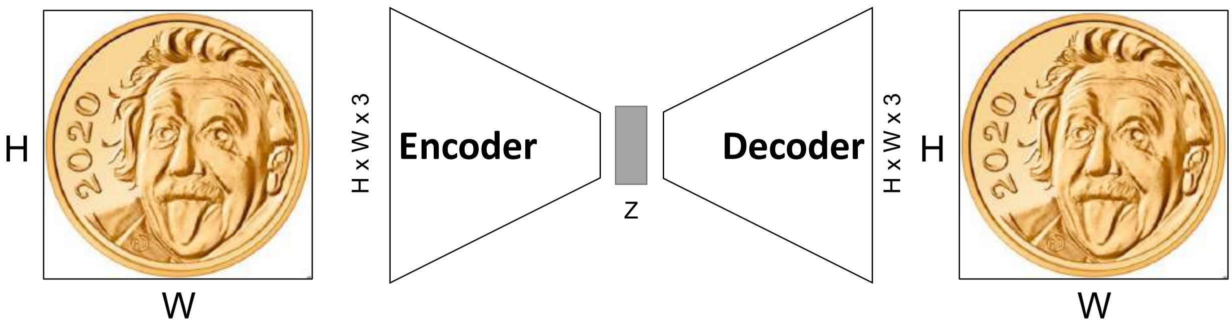
$$
\begin{aligned}
g_1 &= \sigma\left(W_1 \cdot x_t + U_1 \cdot h_{t-1}\right), \\
g_2 &= \sigma\left(W_2 \cdot x_t + U_2 \cdot h_{t-1}\right), \\
g_3 &= \sigma\left(W_3 \cdot x_t + U_3 \cdot h_{t-1}\right), \\
\tilde{c}_t &= \tanh\left(W_c \cdot x_t + u_c \cdot h_{t-1}\right), \\
c_t &= g_2 \circ c_{t-1} + g_3 \circ \tilde{c}_t, \\
h_t &= g_1 \circ c_t,
\end{aligned}
$$

where g_1, g_2, and g_3 are the gates of the LSTM cell.
1) Assign these gates correctly to the **forget** f, **update** u, and **output** o gates. (1p)
2) What does the value c_t represent in a LSTM? (1p)

Problem 7 **Autoencoder and Network Transfer (11 credits)**

You are given a dataset containing 10,000 RGB images with height H and width W of single coins without any labels or additional information.

To work with the image dataset you build an autoencoder as depicted in the figure below:



The input of the encoder is the images of dimension $(H \times W \times 3)$ which are transformed into a one-dimensional real vector with z entries. The latent code is used to decode the input image with the same dimension $(H \times W \times 3)$. Both encoder and decoder are neural networks and the combined network is trainable and uses the L_2 loss as its optimization function.

a) Is an autoencoder an example of unsupervised learning or supervised learning?

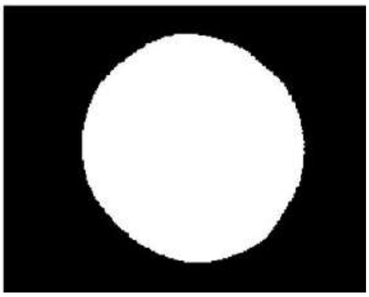
b) As the data gets scaled down from the original dimension to a lower-dimensional bottleneck, an autoencoder can be used for data compression. How does an autoencoder as described above differ from linear methods to reduce the dimensionality of the data such as PCA (principal component analysis)?

c) For an autoencoder we can vary the size of the bottleneck. Discuss briefly what may happen if

i) the latent space is *too small* (1p).

ii) the latent space is *too big* (1pt)

d) Now, you want to generate a random image of a coin. To do so, can you just randomly sample a vector from the latent space to generate a new coin image?



e) Now, someone gives you 1,000 images that are annotated for semantic segmentation of coin and background as shown in the image above. How would you change the architecture of the discussed autoencoder network to perform semantic segmentation?

f) If you wanted to train the new semantic segmentation network what loss function would you use and how?

g) How would you leverage your pretrained autoencoder for training a new segmentation network efficiently?

h) Why do you expect the pretrained autoencoder variant to generalize more than a randomly initialized network?

Problem 8 **Unsorted Short Questions (11 credits)**

a) Why do we need activation functions in our neural networks?

0 1

b) You are solving the binary classification task of classifying images as cars vs. persons. You design a CNN with a single output neuron. Let the output of this neuron be z. The final output of your network, $\hat{y}$ is given by:

$$\hat{y} = \sigma\left(ReLU(z)\right),$$

where σ denotes the sigmoid function. You classify all inputs with a final value $\hat{y} \geq 0.5$ as car images. What problem are you going to encounter?

0 1

c) Suggest a method to solve exploding gradients when training fully-connected neural networks.

0 1

d)

Was a badly phrased question. Removed.

0 1

e) Why do we often refer to $L2$-regularization as "weight decay"? Derive a the mathematical expression that includes the weights W, the learning rate η, and the $L2$-regularization hyperparameter λ to explain your point.

0 1 2 3

0 1 2 3 4

f) You are given input samples $\mathbf{x} = (x_1, \dots, x_n)$ for which each component x_j is drawn from a distribution with zero mean. For an input vector $\mathbf{x}$ the output $\mathbf{s} = (s_1, \dots, s_n)$ is given by

$$s_i = \sum_{j=1}^{n} w_{ij} \cdot x_j,$$

where your weights $\mathbf{w}$ are inititalized by a uniform random distribution $U(-\alpha, \alpha)$.

How do you have to choose α such that the variance of the input data and the output is identical, hence $\mathrm{Var}(s) = \mathrm{Var}(x)$?

Hints: For two statistically independent variables X and Y holds:

$$\mathrm{Var}(X \cdot Y) = \left[\mathrm{E}(X)\right]^2 \mathrm{Var}(Y) + \left[\mathrm{E}(Y)\right]^2 \mathrm{Var}(X) + \mathrm{Var}(X)\mathrm{Var}(Y)$$

Furthermore the PDF of an uniform distribution $U(a, b)$ is

$$f(x) = \begin{cases} \frac{1}{b-a} & \text{for } x \in [a, b] \\ 0 & \text{otherwise.} \end{cases}$$

The variance of a continuous distribution is calculated as

$$\mathrm{Var}(X) = \int_R x^2 f(x)\, dx - \mu^2,$$

where μ is the expected value of X.

Bonus question: Too complex.

Additional space for solutions–clearly mark the (sub)problem your answers are related to and strike out invalid solutions.