VIR 2019 **Name:** ____________________

Exam test

Variant: B Points ____________________

1. Consider the following network.

$$y = \cos(\mathbf{w}^\top \mathbf{x}) + b \tag{1}$$

- Draw the computational graph of the forward pass of this network. Note that **every** operator is a node with a given arity and output. For example, the + operator is a node which has two input arguments and a single output argument, etc...

- Consider an input $\mathbf{x} = [0, 2]\mathbf{w} = [\pi, \frac{\pi}{2}], b = 1$ and label $l = 1$.
  - Compute the forward pass of the network.
  - Use an L_2 loss (Mean square error) to compute the loss value between the forward prediction y and label l. Add this loss to the computation graph.
  - Use the chain rule to compute the gradient $\frac{\partial L(y,l)}{\partial \mathbf{w}}$ and estimate an update of parameters $\mathbf{w}$ with learning rate $\alpha = 0.8$.

2. Consider a convolutional neural network layer l_1 which maps an RGB image of size 256×256 to 16 feature maps having the half of the spatial dimensions as the image. The kernel size is 3×3 and uses a stride 2.

    - What is the size of padding, which ensure the same spatial resolution of the output feature map?

    - How much memory (in bytes) do kernel weights in layer l_1 take up, assuming `float32` weights? Ignore the *bias* weights.

    - How many mathematical operations does this layer perform for a single forward pass. A multiplication or addition of two numbers can be considered as one operation.

    - Name a technique that improves the basic gradient descent update step which helps prevent getting stuck in shallow local minima and allows better training of deeper models.

3. Activation function maps single input $\mathbf{x}$ on a single output value $\mathbf{y}$.

   - Define a Rectified Linear Unit $\mathbf{relu}(\mathbf{x})$ activation function in pseudocode. The function has a single argument $\mathbf{x}$ and output $\mathbf{y} = \mathbf{relu}(\mathbf{x})$.

   - Define the gradient of the $\mathbf{relu}(\mathbf{x})$ activation function in pseudocode. The function has a single argument $\mathbf{x}$ and outputs $\frac{\partial relu(x)}{\partial \mathbf{x}}$. Hint: Break up the function into two separate cases (if-else).

4. You are given batch of three one-dimensional training examples $x_1 = 3, x_2 = 1, x_3 = 5$.

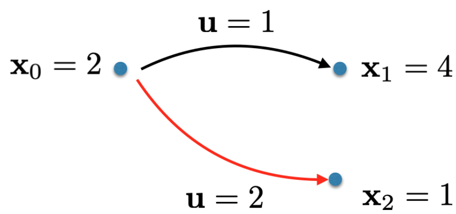
   - Compute output of the batch-norm layer with learnable parameters $\gamma = 2$, $\beta = -3$.

   - Compute gradient of the batch-norm layer with respect to the parameter β.
     Hint: output of the batch-norm layer for this batch is three-dimensional.

5. Consider MDP consisting of three states $\mathbf{x}_0 = 2, \mathbf{x}_1 = 4, \mathbf{x}_2 = 1$ and two types of actions $\mathbf{u} = 1$ and $\mathbf{u} = 2$, see image below. Agent selects action $\mathbf{u}$ in the state $\mathbf{x}$ according the following stochastic policy

$$\pi_\theta(\mathbf{u}|\mathbf{x}) = \begin{cases} \sigma(\theta\mathbf{x}) & \text{if } \mathbf{u} = 1 \\ 1 - \sigma(\theta\mathbf{x}) & \text{if } \mathbf{u} = 2 \end{cases}$$

with scalar parameter $\theta = 3$. This policy maps one-dimensional state $\mathbf{x}$ on the probability distribution of two possible actions $\mathbf{u} = 1$ or $\mathbf{u} = 2$.



Consider trajectory-reward function defined as follows:

$$r(\tau) = \sum_{\mathbf{x}_i \in \tau} \frac{1}{\mathbf{x}_i}$$

Given training trajectory $\tau = [(\mathbf{x}_0 = 2), (\mathbf{u} = 2), (\mathbf{x}_2 = 1)]$, which consists of the single transition (outlined by red color), estimate:

- Policy gradient

$$\frac{\partial \log \pi_\theta(\mathbf{u}|\mathbf{x})}{\partial \theta}\Big|_{\substack{\mathbf{x} = \mathbf{x}_0 \\ \mathbf{u} = \mathbf{u}_0}} \cdot r(\tau) =$$

- Updated weights with learning rate $\alpha = 0.5$

$$\theta^{\text{updated}} =$$