

Date:

| Code             | ITM 528 |           | Title |         | Deep Learning |           |      |
|------------------|---------|-----------|-------|---------|---------------|-----------|------|
| Time for Exam    | 3 hours | Questions |       | 10      |               | Weighting | 35 % |
| Student's Number |         |           |       | Student | 's Name       |           |      |

- 1. (5pts)
- (a) False -> no rule-based approach (data-driven approach is suitable)
- (b) True
- (c) False -> no always guarantee to converge to the global optinum
- (d) True
- (e) True
- 2. (14pts)
- (a) (10pts) Partial score: if appropriate formula derivation is

$$-\log P(\mathbf{y} \,|\, \mathbf{X}) = \sum_{i=1}^{n} \frac{1}{2} \log(2\pi\sigma^2) + \frac{1}{2\sigma^2} \left( y^{(i)} - \mathbf{w}^T \mathbf{x}^{(i)} - b \right)^2$$

- (b) (4pts) Score when strictly describing changes in expressions and relationships with MSE in a fixed variable
- ullet If we assume that  $\sigma$  is fixed, we can ignore the first term.
- In fact, as the solution does not depend on  $\sigma$ , minimizing the mean squared error is equivalent to the maximum likelihood estimation of a linear model under the assumption of additive Gaussian noise.
- 3. (5pts)
- (a) (2pts) overfitting
- (b) (3pts) dropout, weight decay, etc. (No score if simply referred to as regularization.)



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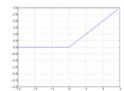
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- 4. (20pts)
- (a) (4pts) 3
- (b) (4pts) 2
- (c) (12pts) The final answer must be expressed in softmax. Description of gradient simulation must be included. Partial score: if appropriate formula derivation is

$$\partial_{o_j} l(\mathbf{y}, \hat{\mathbf{y}}) = \frac{\exp(o_j)}{\sum_{k=1}^q \exp(o_k)} - y_j = \operatorname{softmax}(\mathbf{o})_j - y_j$$

The derivative is the difference between the probability assigned by our model, yhat, and the ground truth label, y. This fact makes computing gradients easy in practice.

- 5. (10pts)
- (a) (2pts)



ReLU activation function helps to prevent the gradient vanishing problem.

(b) (5pts) Partial score: if appropriate calculation equations is

Forward pass:

$$\begin{split} h_1 &= i_1 \times w_{11} + i_2 \times w_{21} + b_1 = 2.0 \times 1.0 - 1.0 \times 0.5 + 0.5 = 2.0 \\ h_2 &= i_1 \times w_{12} + i_2 \times w_{22} + b_2 = 2.0 \times -0.5 + -1.0 \times -1.0 - 0.5 = -0.5 \\ h_3 &= \max(0, h_1) = h_1 = 2 \\ h_4 &= \max(0, h_2) = 0 \\ o_1 &= h_3 \times w_{31} + h_4 \times w_{41} + b_3 = 2 \times 0.5 + 0 \times -0.5 - 1.0 = 0 \\ o_2 &= h_3 \times w_{32} + h_4 \times w_{42} + b_4 = 2 \times -1.0 + 0 \times 1.0 + 0.5 = -1.5 \end{split}$$

(c) (3pts)

$$MSE = \frac{1}{2} \times (t_1 - o_1)^2 + \frac{1}{2} \times (t_2 - o_2)^2 = 0.5 \times 1.0 + 0.5 \times 4.0 = 2.5$$



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6. (20pts, each 4pts) Processing the correct answer without considering the difference in Transpose.

$$\begin{split} & \cdot \frac{\partial J}{\partial \mathbf{W}_2} = \frac{\partial J}{\partial \mathbf{z}_2} \frac{\partial \mathbf{z}_2}{\partial \mathbf{W}_2} = \delta_1 \frac{\partial \mathbf{z}_2}{\partial \mathbf{W}_2} = \delta_1^T \mathbf{h}_1^T \in \mathbb{R}^{n_c \times d_h} \\ & \cdot \frac{\partial J}{\partial \mathbf{b}_2} = \frac{\partial J}{\partial \mathbf{z}_2} \frac{\partial \mathbf{z}_2}{\partial \mathbf{b}_2} = \delta_1 \frac{\partial \mathbf{z}_2}{\partial \mathbf{b}_2} = \delta_1^T \in \mathbb{R}^{n_c \times 1} \\ & \cdot \frac{\partial J}{\partial \mathbf{W}_1} = \frac{\partial J}{\partial \mathbf{z}_1} \frac{\partial \mathbf{z}_1}{\partial \mathbf{W}_1} = \delta_2 \frac{\partial \mathbf{z}_1}{\partial \mathbf{W}_1} = \delta_2^T \mathbf{x}^T \in \mathbb{R}^{d_h \times d_x} \\ & \cdot \frac{\partial J}{\partial \mathbf{b}_1} = \frac{\partial J}{\partial \mathbf{z}_1} \frac{\partial \mathbf{z}_1}{\partial \mathbf{b}_1} = \delta_2 \frac{\partial \mathbf{z}_1}{\partial \mathbf{b}_1} = \delta_2^T \mathbf{I}^T = \delta_2^T \in \mathbb{R}^{d_h \times 1} \\ & \cdot \frac{\partial J}{\partial \mathbf{x}} = \frac{\partial J}{\partial \mathbf{z}_1} \frac{\partial \mathbf{z}_1}{\partial \mathbf{x}} = \mathbf{W}^T \delta_2^T \in \mathbb{R}^{d_x \times 1} \end{split}$$

### 7. (6pts)

#### (a) (2pts)

Padding helps preserve the spatial dimensions of the input after convolution, preventing the output from shrinking. It also allows for edge features to be captured better.

#### (b) (2pts)

Increasing the stride reduces the size of the output feature map, as the convolutional filter skips more elements in the input.

#### (c) (2pts)

Transposed Convolution is an operation used to reverse the downsampling effect caused by regular convolution. It takes a small input feature map and reconstructs it into a larger one, often called "upsampling."



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8. (6pts) You will be deducted when you write the correct answer

$$\begin{bmatrix} 1 & 3 \\ 5 & 6 \end{bmatrix} \quad \Rightarrow \quad \max(1, 3, 5, 6) = 6$$

$$\begin{bmatrix} 2 & 4 \\ 7 & 8 \end{bmatrix} \quad \Rightarrow \quad \max(2,4,7,8) = 8$$

$$\begin{bmatrix} 9 & 2 \\ 4 & 3 \end{bmatrix} \quad \Rightarrow \quad \max(9, 2, 4, 3) = 9$$

$$\begin{bmatrix} 1 & 5 \\ 6 & 7 \end{bmatrix} \quad \Rightarrow \quad \max(1,5,6,7) = 7$$

$$Output = \begin{bmatrix} 6 & 8 \\ 9 & 7 \end{bmatrix}$$

9. (8pts)

(a) (3pts)

32x3x3x64 = 18,432

(b) (3pts)

32x1x1x5 = 160 5x3x3x64 = 2,880 Total = 3,040

(c) (2pts)

Reduce number of parameters, 18,432 >>>2,880.

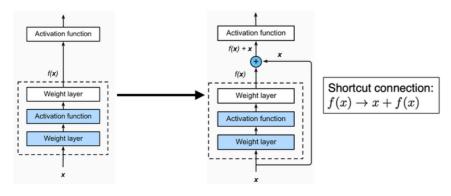


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10. (6pts)

### (a) (3pts)



### (b) (3pts)

In a residual block, we add what's called an identity map, also known as a shortcut connection. Instead of learning a new function completely from scratch, the shortcut allows the model to pass the input, identity x directly through to the output and only learn the difference, f(x). This makes training easier and prevents problems like degradation in very deep networks.