Group	Name	67	68	69	70	71	71	73	74	75	$\sum$
	Svetlana Seliunina										
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Technical Neural Networks Assignment Sheet 11

January 2023

Assignment 67

Up until now we gained 196 points in both written and programming assignments, so we exceed the threshold of 146 points. Also both of us presented twice, therefore should already be admitted to the exam.

Assignment 68

Performing BP, every temporal copy of the network will get a different weight change for the same weight, although we would like to have corresponding weights to be identical. The method to deal with this, is to accumulate the different weight changes for the very weights, and to do the weight update according to the sum of weight changes

Assignment 69

Elman network is a Jordan network when all weights of context neurons in hidden layers are set to zero, so that only context neurons in the input layer contribute. Also weights λ should be set to 0.

Assignment 70

The authors provide a method for combining deep learning and classical feature based models using a Multi-Layer Perceptron (MLP) network for financial sentiment analysis.

Md Shad Akhtar, Abhishek Kumar, Deepanway Ghosal, Asif Ekbal, and Pushpak Bhattacharyya. 2017. A Multilayer Perceptron based Ensemble Technique for Fine-grained Financial Sentiment Analysis. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 540–546, Copenhagen, Denmark. Association for Computational Linguistics.

Assignment 71

Hopfield Networks can not distinguish between a pattern and it's inverse pattern refers to the fact that the state of the Hopfield neuron depends on the state of its neighbors. If the pattern is the same, but reverse, the neighbors of the neuron are not changed so it will yield the same result.

Assignment 72

Assignment 73

In autoassociator mode pattern is associated to itself, so the weights are symmetric: $w_{jk} = x_j x_k = w_{kj}$.
In heteroassociator mode networks associate one pattern with the next one, so the weights are not symmetric: $w_{jk} = x_j^p x_k^q \neq w_{kj}$.

Assignment 74

As the dynamic is asynchronous, only one unit is evaluated each time. If the k^{th} unit is selected, there are two options:

- k does not change state. - k changes state (-1 to 1 / 1 to -1)

In the first case, the energy function remains the same, $E(t+1) = E(t)$. Else the energy function changes, according to the new excitation value x_k' of the k^{th} unit. The difference of the energy of the system is given by:

$$E(x) - E\left(x'\right) = \left(-\sum_{j=1}^{n} w_{kj} x_j x_k + \theta_k x_k\right) - \left(-\sum_{j=1}^{n} w_{kj} x_j x_k' + \theta_k x_k'\right)$$

Since we know that $w_{kk} = 0, E(x) - E\left(x'\right) = -\left(x_k - x_k'\right) \cdot \left(\sum_{j=1}^{n} w_{kj} x_j - \theta_k\right)$

The second term of this equation is the excitation e_k of the k^{th} unit. The unit changes its state, so the excitation has a different sign than x_k and $-x_k'$ according to the transfer function. Therefor $E(x) > E\left(x'\right)$. The energy function will decrease for every change, and since there is only a finite number of possible states, the network should reach a state where the energy cannot decrease more, it will be a stable state.

Assignment 75

In autoassociator mode learning rule for multiple patterns is $w_{ij} = \sum x_i^p x_j^p$ and $w_{ii} = 0$. Matrix W will look like:

```
[[ 0.  2.  2. -2.  0. -2. -2. -2.]
 [ 2.  0.  0.  0. -2.  0. -4.  0.]
 [ 2.  0.  0.  0. -2. -4.  0.  0.]
 [-2.  0.  0.  0. -2.  0.  0.  0.]
 [ 0. -2. -2. -2.  0.  2.  2. -2.]
 [-2.  0. -4.  0.  2.  0.  0.  0.]
 [-2. -4.  0.  0.  2.  0.  0.  0.]
 [-2.  0.  0.  0. -2.  0.  0.  0.]]
```