COMP4211 - Machine Learning

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Problem Set

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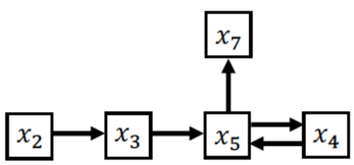
Problem 1.

(1)



Write your answer

Incoming Matrix: A^I

	2	3	5	4	7
2	0	0	0	0	0
3	1	0	0	0	0
5	0	1/2	0	1/2	0
4	0	0	1	0	0
7	0	0	1	0	0

Outgoing Matrix: A^O

	2	3	5	4	7
2	0	1	0	0	0
3	0	0	1	0	0
5	0	0	0	1/2	1/2
4	0	0	1	0	0
7	0	0	0	0	0

(2) ${h^{l-1}}^\top \in \mathbb{R}^d$ and ${h^{l-1}}^\top \mathbf{W}^I \in \mathbb{R}^d$, so $\mathbf{W}^I \in \mathbb{R}^{d\times d}$

${h^{l-1}}^\top \in \mathbb{R}^d$ and ${h^{l-1}}^\top \mathbf{W}^O \in \mathbb{R}^d$, so $\mathbf{W}^O \in \mathbb{R}^{d\times d}$

Thus $\mathbf{W}^I, \mathbf{W}^O$ both have d^2 parameters.

(3) $a_i^l \in \mathbb{R}^{2d\times 1}$ and $\mathbf{W}_z a_i^l \in \mathbb{R}^{d\times 1}$, so $\mathbf{W}_z \in \mathbb{R}^{d\times 2d}$

$a_i^l \in \mathbb{R}^{2d\times 1}$ and $\mathbf{W}_r a_i^l \in \mathbb{R}^{d\times 1}$, so $\mathbf{W}_r \in \mathbb{R}^{d\times 2d}$

$a_i^l \in \mathbb{R}^{2d\times 1}$ and $\mathbf{W}_h a_i^l \in \mathbb{R}^{d\times 1}$, so $\mathbf{W}_h \in \mathbb{R}^{d\times 2d}$

Thus $\mathbf{W}_z, \mathbf{W}_r, \mathbf{W}_h$ all have $2d^2$ parameters.

$h_i^{l-1} \in \mathbb{R}^{d\times 1}$ and $\mathbf{U}_z h_i^{l-1} \in \mathbb{R}^{d\times 1}$, so $\mathbf{W}_z \in \mathbb{R}^{d\times d}$

$h_i^{l-1} \in \mathbb{R}^{d\times 1}$ and $\mathbf{U}_r h_i^{l-1} \in \mathbb{R}^{d\times 1}$, so $\mathbf{W}_r \in \mathbb{R}^{d\times d}$

$r_i^l \odot h_i^{l-1} \in \mathbb{R}^{d\times 1}$ and $\mathbf{U}_h \left(r_i^l \odot h_i^{l-1}\right) \in \mathbb{R}^{d\times 1}$, so $\mathbf{W}_h \in \mathbb{R}^{d\times d}$

Thus $\mathbf{U}_z, \mathbf{U}_r, \mathbf{U}_h$ all have d^2 parameters.

(4) Experiments to demonstrate the effectiveness of CGNN

- I will train and test the CGNN model on real-world datasets such as MovieLens and Amazon product reviews and compare its performance against baseline recommendation models like matrix factorization and collaborative filtering.
- I will conduct ablation studies to assess various components of CGNN, so I'll be able to better understand its functionality.
- To evaluate the robustness of CGNN, I will test it with inputs that vary in session lengths and item diversity. For example, one sequence may consist of a a few copies of only one or two items, while another sequence may contain entirely different items.

Methods to prevent overfitting in CGNN

- Introduce dropout layers or use regularization techniques.
- Randomly modify the input data, either by adding new items or modifying existing items, to increase robustness.

(5) $\mathbf{W}^I, \mathbf{W}^O$ have a total of $2d^2$ parameters.

$\mathbf{b}^I, \mathbf{b}^O \in \mathbb{R}^d$ have a total of $2d$ parameters.

$\mathbf{W}_z, \mathbf{W}_r, \mathbf{W}_h$ have a total of $6d^2$ parameters.

$\mathbf{U}_z, \mathbf{U}_r, \mathbf{U}_h$ have a total of $3d^2$ parameters.

$\mathbf{W}_{q1}, \mathbf{W}_{q2}$ have the same shapes as $\mathbf{W}_{k1}, \mathbf{W}_{k2}$, so they have a total of $6d^2$ parameters.

Summing these up, we get $2d^2 + 2d + 6d^2 + 3d^2 + 6d^2 = 17d^2 + 2d = 170200$ parameters.

Problem 2.

$e^{(0)} \in \mathbb{R}^{100}, e^{(1)} \in \mathbb{R}^{80}, e^{(2)} \in \mathbb{R}^{40}, e^{(3)} \in \mathbb{R}^{20}$, so

$$\begin{aligned}
&\mathbf{W}_1^{(1)} \in \mathbb{R}^{80\times 100}, \quad \mathbf{W}_2^{(1)} \in \mathbb{R}^{80\times 100}, \quad \mathbf{W}_3^{(1)} \in \mathbb{R}^{80\times 200} \\
&\mathbf{W}_1^{(2)} \in \mathbb{R}^{40\times 80}, \quad \mathbf{W}_2^{(2)} \in \mathbb{R}^{40\times 80}, \quad \mathbf{W}_3^{(2)} \in \mathbb{R}^{40\times 160} \\
&\mathbf{W}_1^{(3)} \in \mathbb{R}^{20\times 40}, \quad \mathbf{W}_2^{(3)} \in \mathbb{R}^{20\times 40}, \quad \mathbf{W}_3^{(3)} \in \mathbb{R}^{20\times 80}
\end{aligned}$$

Therefore, we have a total of $80 \cdot 400 + 40 \cdot 320 + 20 \cdot 160 = 48000$ parameters.