Brain-Inspired Continual Learning

Liyuan Wang

School of Life Sciences
Department of Computer Science and Technology
Tsinghua University
Continual / Incremental / Lifelong Learning

- New Task / Class, New Instance, New Domain
- Catastrophic Forgetting
- Stability-Plasticity Trade-off

Continual Learning is Getting Hotter and Hotter

Top Keywords

ICLR 2022

McCloskey et al., 1989; McClelland et al., 1995
(Brain-Inspired) Continual Learning Approaches

- **Regularization-Based Methods**
  - Selectively Penalize Parameter Changes, Fast-Slow Weights
  - Synaptic Consolidation, Synaptic Plasticity

- **Replay-Based Methods**
  - Old / Generated Data, Old / Generated Feature
  - Biological Memory Replay, Complementary Learning System

- **Architecture-Based Methods**
  - Parameter Isolation, Sub-modules / Sub-networks
  - Modularization, Neural Inhibition, Engram Ensemble
Triple Memory Networks: A Brain-Inspired Framework

The Brain Memory System

Triple Memory Networks

Liyuan Wang, Bo Lei, Qian Li, Hang Su, Jun Zhu, Yi Zhong. TNNLS, 2021.
## Experimental Results

Without accessing to the old data, Triple Memory Networks (TMNs) achieve the state-of-the-art performance in supervised class-incremental learning.

<table>
<thead>
<tr>
<th>Methods</th>
<th>MNIST $A_5$</th>
<th>MNIST $A_{10}$</th>
<th>SVHN $A_5$</th>
<th>SVHN $A_{10}$</th>
<th>CIFAR-10 $A_5$</th>
<th>CIFAR-10 $A_{10}$</th>
<th>ImageNet-50 $A_{30}$</th>
<th>ImageNet-50 $A_{50}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Joint Training</td>
<td>99.87</td>
<td>99.24</td>
<td>92.99</td>
<td>88.72</td>
<td>83.40</td>
<td>77.82</td>
<td>57.35</td>
<td>49.88</td>
</tr>
<tr>
<td>EWC-S [13]</td>
<td>79.36</td>
<td>60.83</td>
<td>38.65</td>
<td>25.36</td>
<td>37.39</td>
<td>21.13</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>SI-S [14]</td>
<td>78.40</td>
<td>60.18</td>
<td>37.21</td>
<td>23.86</td>
<td>36.96</td>
<td>20.16</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>RWalk-S [25]</td>
<td>82.08</td>
<td>62.84</td>
<td>39.25</td>
<td>26.63</td>
<td>35.75</td>
<td>22.27</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>MAS-S [15]</td>
<td>80.40</td>
<td>67.66</td>
<td>37.57</td>
<td>25.11</td>
<td>44.38</td>
<td>19.56</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>iCarl [18]</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>57.30</td>
<td>43.69</td>
<td>29.38</td>
<td><strong>28.98</strong></td>
</tr>
<tr>
<td>DGMw-S [22]</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>36.87</td>
<td>18.84</td>
</tr>
<tr>
<td>EWC-M [41]</td>
<td>70.62</td>
<td>77.03</td>
<td>39.84</td>
<td>33.02</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>DGR [3]</td>
<td>90.39</td>
<td>85.40</td>
<td>61.29</td>
<td>47.28</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>MeRGAN [21]</td>
<td>98.19</td>
<td><strong>97.00</strong></td>
<td>80.90</td>
<td>66.78</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>DGMw [22]</td>
<td>98.75</td>
<td>96.46</td>
<td>83.93</td>
<td>74.38</td>
<td>72.45</td>
<td>56.21</td>
<td>32.14</td>
<td>17.82</td>
</tr>
<tr>
<td>TMNs (ours)</td>
<td><strong>98.80</strong></td>
<td>96.72</td>
<td><strong>87.12</strong></td>
<td><strong>77.08</strong></td>
<td><strong>72.72</strong></td>
<td><strong>61.24</strong></td>
<td><strong>38.23</strong></td>
<td>28.08</td>
</tr>
</tbody>
</table>
**ORDisCo: Semi-supervised Continual Learning**

- The incremental data are typically partially-labeled in realistic scenarios.
- Representative methods lack the ability to exploit the incremental unlabeled data.

Liyuan Wang, Kuo Yang, Chongxuan Li, Lanqing Hong, Zhenguo Li, Jun Zhu. CVPR 2021.
Experimental Results

**Classification**

- **SVHN-1**
  - SMB
  - SMB+UMB
  - SMB+UMB+UC
  - ORDisCo

- **CIFAR10-5**
  - SMB
  - SMB+UMB
  - SMB+UMB+UC
  - ORDisCo

**Conditional Generation**

- **SMB**
- **ORDisCo**

SMB: Replay of Supervised Memory Buffer
UMB: Replay of Unsupervised Memory Buffer
Memory Replay with Compression

\[
\mathcal{P}_q(M^c_q | D) = \frac{\det(L_{M^c_q}(D; q, \theta))}{\sum_{|M| = N^m_q} \det(L_M(D; q, \theta))},
\]

(1) Maximize \( \mathcal{P}_q(M^*_q | D) \quad \frac{\mathcal{P}_q(M^c_q | D)}{\mathcal{P}_q(M^*_q | D)} \leq \mathcal{P}_q(M^*_q | D) \)

(2) Constrain that \( \mathcal{P}_q(M^c_q | D) \) is consistent with \( \mathcal{P}_q(M^*_q | D) \)

\[
L_2(q) = \left| \frac{\mathcal{P}_q(M^c_q | D)}{\mathcal{P}_q(M^*_q | D)} - 1 \right| = \left| \frac{\det(M^c_q^T M^c_q)}{\det(M^*_q^T M^*_q)} Z_q - 1 \right|
\]

\[
= \left| \left( \frac{\text{Vol}^c_q}{\text{Vol}^*_q} \right)^2 Z_q - 1 \right| = \left| R^2_q Z_q - 1 \right|
\]

Liyuan Wang, Xingxing Zhang, Kuo Yang, Longhui Yu, Chongxuan Li, Lanqing Hong, Shifeng Zhang, Zhenguo Li, Yi Zhong, Jun Zhu. ICLR 2022.
Memory Replay with Compression

Given a limited storage space, our method can efficiently determine a proper compression quality for incoming data, without repetitive training.
Experimental Results

Large-Scale Class-Incremental Learning

Object Detection for Autonomous Driving

<table>
<thead>
<tr>
<th>Method</th>
<th>AP</th>
<th>AP_{50}</th>
<th>AP_{75}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pseudo</td>
<td>40.36</td>
<td>63.83</td>
<td>43.82</td>
</tr>
<tr>
<td>Labeling</td>
<td>40.75/0.39</td>
<td>65.11/1.28</td>
<td>43.53/-0.29</td>
</tr>
<tr>
<td>Ours</td>
<td>41.50/1.14</td>
<td>65.36/1.53</td>
<td>44.95/1.13</td>
</tr>
<tr>
<td>Unbiased</td>
<td>42.88</td>
<td>66.70</td>
<td>45.99</td>
</tr>
<tr>
<td>Teacher</td>
<td>43.10/0.22</td>
<td>66.88/0.18</td>
<td>46.62/0.63</td>
</tr>
<tr>
<td>Ours</td>
<td>43.72/0.84</td>
<td>67.80/1.10</td>
<td>47.36/1.37</td>
</tr>
</tbody>
</table>
AFEC: Active Forgetting of Negative Transfer

- If the old knowledge conflicts with the new task learning, then precisely remembering the old knowledge will further aggravate the interference.
- Biological neural networks can actively forget the conflicting information, through regulating the learning-triggered synaptic expansion and synaptic convergence.

Liyuan Wang, Mingtian Zhang, Zhongfan Jia, Qian Li, Chenglong Bao, Kaisheng Ma, Jun Zhu, Yi Zhong. NeurIPS, 2021
AFEC: Active Forgetting of Negative Transfer

- We introduce a forgetting factor $\beta$ and replace the posterior that absorbs all the information of the old tasks by a weighted product distribution:

$$p(\theta|D_A^{train}) = \frac{p(D_A^{train}|\theta)p(\theta)}{p(D_A^{train})}$$

$$p_m(\theta|D_A^{train}, \beta) = \frac{p(\theta|D_A^{train})^{(1-\beta)}p(\theta)^\beta}{Z}$$

- The optimal forgetting factor can maximize the learning of each new task:

$$\beta^* = \arg\max_\beta p(D_B^{train}|D_A^{train}, \beta)$$

$$= \arg\max_\beta \int p(D_B^{train}|\theta)p_m(\theta|D_A^{train}, \beta)d\theta$$
### Experimental Results

<table>
<thead>
<tr>
<th>Methods</th>
<th>CIFAR100-SC</th>
<th>CIFAR100</th>
<th>CIFAR10/100</th>
<th>CUB-200 w/ PT</th>
<th>CUB-200 w/o PT</th>
<th>ImageNet-100</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$A_{10}$</td>
<td>$A_{20}$</td>
<td>$A_{10}$</td>
<td>$A_{20}$</td>
<td>$A_2$</td>
<td>$A_{2+20}$</td>
</tr>
<tr>
<td>EWC [13]</td>
<td>52.25</td>
<td>51.74</td>
<td>68.72</td>
<td>69.18</td>
<td>85.07</td>
<td>77.75</td>
</tr>
<tr>
<td>* AFEC (ours)</td>
<td><strong>56.28</strong></td>
<td><strong>55.24</strong></td>
<td><strong>72.36</strong></td>
<td><strong>72.29</strong></td>
<td><strong>86.87</strong></td>
<td><strong>81.25</strong></td>
</tr>
<tr>
<td>MAS [1]</td>
<td>52.76</td>
<td>52.18</td>
<td>67.60</td>
<td>69.41</td>
<td>84.97</td>
<td>77.39</td>
</tr>
<tr>
<td>w/ AFEC (ours)</td>
<td>55.26</td>
<td>54.89</td>
<td>69.57</td>
<td>71.20</td>
<td>86.21</td>
<td>80.01</td>
</tr>
<tr>
<td>SI [36]</td>
<td>52.20</td>
<td>51.97</td>
<td>68.72</td>
<td>69.21</td>
<td>85.00</td>
<td>76.69</td>
</tr>
<tr>
<td>w/ AFEC (ours)</td>
<td>55.25</td>
<td>53.90</td>
<td>69.34</td>
<td>70.13</td>
<td>85.71</td>
<td>78.49</td>
</tr>
<tr>
<td>RWALK [2]</td>
<td>50.51</td>
<td>49.62</td>
<td>66.02</td>
<td>66.90</td>
<td>85.59</td>
<td>73.64</td>
</tr>
<tr>
<td>w/ AFEC (ours)</td>
<td>52.62</td>
<td>51.76</td>
<td>68.50</td>
<td>69.12</td>
<td>86.12</td>
<td>77.16</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>fruit and vegetables</th>
<th>large carnivores</th>
<th>small mammals</th>
<th>household furniture</th>
<th>vehicle 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image</td>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="image4.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
</tr>
<tr>
<td>EWC</td>
<td><img src="image6.png" alt="Image" /></td>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
<td><img src="image9.png" alt="Image" /></td>
<td><img src="image10.png" alt="Image" /></td>
</tr>
<tr>
<td>AFEC</td>
<td><img src="image11.png" alt="Image" /></td>
<td><img src="image12.png" alt="Image" /></td>
<td><img src="image13.png" alt="Image" /></td>
<td><img src="image14.png" alt="Image" /></td>
<td><img src="image15.png" alt="Image" /></td>
</tr>
</tbody>
</table>
Experimental Results

New Task

Old Task
Summary

- Continual learning is complex, but all roads lead to Rome;

- Successful biological strategies can provide inspirations for and evolve with computational models;

- Order is the appearance, compatibility is the goal;

- Look to the stars (general theoretical insights) and keep feet on the ground (realistic challenges).
Acknowledgement

School of Life Sciences in Tsinghua:
   Prof. Yi Zhong, Prof. Qian Li

Dept. of Comp. Sci. & Tech. in Tsinghua:
   Prof. Jun Zhu, Dr. Chongxuan Li (now at Renmin U), Dr. Xingxing Zhang

Brain-inspire AI Project:
   Prof. Kaisheng Ma, Prof. Chenglong Bao, Zhongfan Jia

Huawei Noah's Ark Lab:
   Dr. Lanqing Hong, Dr. Zhengu Li, Kuo Yang, Mingtian Zhang, Longhui Yu