

要点

- memorization effect + critical parameters
- 减弱了early stopping 之前wrong label对模型的影响
- 将网络参数分为关键参数和非关键参数，用不同的方式学习两种参数

方法

关键参数和非关键参数

关键参数和非关键参数的区别

*lottery ticket hypothesis *表明，深层网络可能被过度参数化，并且只有关键参数对于泛化是重要的；非关键参数的不是简单模式，而是一些小模式（这样会使得模型过拟合）

关键参数和非关键参数的划分

$$G'(1) = \nabla L(\mathcal{W}; S)^\top \mathcal{W} = \langle \nabla L(\mathcal{W}; S), \mathcal{W} \rangle.$$

因为损失函数高维不好分析，因此只能分析 $G'(1)$ 。当 $G'(1) = 0$ 时不能推出模型已经最优，但是最优模型可以推出 $G'(1) = 0$

对于单个参数：

$$g_i = |\nabla L(\mathbf{w}_i; S) \times \mathbf{w}_i|, i \in [m].$$

因为在早期训练时关键参数负责因此在早期训练时 g_i 取值大的参数是关键参数，其他是非关键参数。取最大的 $(1 - \tau)m$ 个参数作为关键参数，其余为非关键参数（ τ 为噪声率）

不同的更新

$$\mathcal{W}_c(k+1) \leftarrow \mathcal{W}_c(k) - \eta \left((1 - \tau) \frac{\partial L(\mathcal{W}_c(k); \tilde{S}^*)}{\partial \mathcal{W}_c(k)} + \lambda \text{sgn}(\mathcal{W}_c(k)) \right),$$

关键参数正常更新

$$\mathcal{W}_n(k+1) \leftarrow \mathcal{W}_n(k) - \eta \lambda \text{sgn}(\mathcal{W}_n(k)).$$

非关键参数用权重衰减抑制

实验

t%

| Dataset | Method | Symmetric | | Asymmetric | | Pairflip | | Instance | |
|-----------|--------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| | | 20% | 40% | 20% | 40% | 20% | 40% | 20% | 40% |
| MNIST | CE | 98.60±0.07 | 98.18±0.16 | 99.00±0.08 | 98.31±0.28 | 98.74±0.17 | 94.08±0.93 | 98.14±0.02 | 92.76±0.21 |
| | GCE | 98.84±0.12 | 98.12±0.33 | 98.92±0.09 | 98.31±0.27 | 98.94±0.05 | 97.39±0.62 | 98.17±0.08 | 94.97±0.32 |
| | DMI | 98.94±0.02 | 98.62±0.17 | 99.07±0.10 | 98.61±0.26 | 98.96±0.12 | 97.27±0.39 | 98.34±0.17 | 95.34±0.28 |
| | APL | 98.74±0.09 | 97.04±0.35 | 98.90±0.07 | 97.23±0.73 | 98.24±0.39 | 95.24±1.49 | 97.03±0.29 | 90.04±3.93 |
| | MentorNet | 97.21±0.13 | 93.96±0.76 | 98.51±0.09 | 93.47±0.80 | 97.25±0.32 | 93.27±0.73 | 95.17±0.26 | 90.05±1.43 |
| | Co-teaching | 97.22±0.18 | 94.64±0.33 | 98.63±0.12 | 93.62±1.27 | 97.44±0.26 | 94.81±0.45 | 97.32±0.15 | 92.45±0.59 |
| | Co-teaching+ | 98.11±0.07 | 95.87±0.27 | 98.83±0.08 | 96.65±1.73 | 98.81±0.12 | 95.42±0.33 | 98.07±0.12 | 94.37±0.48 |
| | S2E | 98.93±0.39 | 93.23±2.37 | 99.23±0.07 | 98.31±0.13 | 99.10±0.04 | 80.15±3.78 | 98.42±0.47 | 83.38±0.94 |
| | Forward | 98.10±0.12 | 96.83±0.28 | 98.79±0.28 | 97.94±0.47 | 98.62±0.16 | 95.37±0.70 | 97.87±0.21 | 92.30±0.18 |
| | T-Revision | 98.93±0.07 | 98.40±0.53 | 99.05±0.16 | 98.23±0.54 | 98.82±0.07 | 97.43±0.19 | 98.33±0.15 | 95.64±0.34 |
| | Joint | 98.54±0.13 | 98.30±0.28 | 98.96±0.05 | 98.40±0.11 | 98.70±0.08 | 96.33±0.82 | 98.11±0.13 | 93.15±0.43 |
| | CDR | 99.00±0.04 | 98.80±0.12 | 99.30±0.04 | 98.80±0.17 | 99.17±0.08 | 98.12±0.23 | 98.49±0.09 | 94.45±1.04 |
| F-MNIST | CE | 90.36±0.21 | 87.61±0.72 | 91.31±0.13 | 86.43±2.01 | 91.65±0.12 | 76.42±4.13 | 88.81±0.67 | 78.62±2.92 |
| | GCE | 91.77±0.13 | 90.02±0.37 | 91.45±0.29 | 73.62±2.92 | 91.99±0.36 | 84.21±2.05 | 91.06±0.55 | 74.82±0.94 |
| | DMI | 91.87±0.26 | 88.65±0.37 | 92.33±0.11 | 89.62±0.48 | 91.33±0.37 | 83.93±0.92 | 90.87±0.15 | 80.51±0.66 |
| | APL | 87.23±0.19 | 73.62±0.88 | 86.21±0.24 | 81.03±3.09 | 84.52±0.73 | 76.39±2.85 | 84.38±0.70 | 60.38±8.37 |
| | MentorNet | 88.12±0.12 | 86.05±0.27 | 89.76±0.18 | 68.93±3.20 | 87.39±0.57 | 76.90±5.72 | 86.50±0.26 | 78.37±0.95 |
| | Co-teaching | 89.03±0.32 | 87.04±0.69 | 92.03±0.16 | 72.23±4.38 | 89.63±0.78 | 84.10±0.92 | 89.27±0.86 | 83.49±1.27 |
| | Co-teaching+ | 91.34±0.17 | 90.23±0.21 | 83.98±1.05 | 66.27±3.01 | 91.08±0.25 | 72.65±0.49 | 83.78±0.73 | 38.79±9.93 |
| | S2E | 90.89±0.27 | 75.68±3.73 | 91.20±0.31 | 87.06±0.50 | 91.52±0.19 | 72.09±2.15 | 89.17±0.32 | 72.62±2.73 |
| | Forward | 90.72±0.19 | 88.05±0.73 | 92.05±0.21 | 85.42±0.74 | 90.02±0.87 | 83.06±0.79 | 87.95±0.75 | 75.34±1.89 |
| | T-Revision | 91.95±0.20 | 90.35±0.28 | 92.07±0.11 | 88.53±0.32 | 91.06±0.19 | 85.67±0.88 | 91.05±0.28 | 84.34±1.37 |
| | Joint | 82.01±0.77 | 72.36±2.84 | 85.92±0.83 | 73.09±0.91 | 86.04±0.99 | 70.87±3.95 | 82.07±0.94 | 50.62±4.77 |
| | CDR | 92.24±0.11 | 90.91±0.27 | 93.01±0.14 | 90.37±0.32 | 93.06±0.19 | 87.55±1.07 | 91.52±0.17 | 85.04±1.02 |
| CIFAR-10 | CE | 89.14±0.41 | 86.25±1.32 | 88.21±0.19 | 86.37±1.03 | 89.68±0.72 | 86.53±0.37 | 86.73±0.36 | 75.33±2.72 |
| | GCE | 89.48±0.28 | 86.07±0.41 | 89.03±0.21 | 84.12±1.24 | 88.58±0.34 | 83.23±3.98 | 88.02±0.34 | 76.89±0.96 |
| | DMI | 89.29±0.30 | 86.89±1.07 | 89.37±0.82 | 86.32±1.17 | 88.41±1.01 | 84.02±1.73 | 88.93±0.29 | 79.35±2.17 |
| | APL | 88.21±0.32 | 81.07±1.36 | 89.03±0.75 | 85.10±2.42 | 87.34±1.44 | 80.12±3.65 | 76.31±2.24 | 50.73±4.89 |
| | MentorNet | 83.26±0.72 | 78.37±1.73 | 84.07±0.59 | 60.22±3.47 | 78.73±0.89 | 69.37±3.28 | 83.06±0.92 | 73.40±2.19 |
| | Co-teaching | 88.20±0.27 | 84.45±0.68 | 87.42±0.38 | 64.03±0.73 | 82.66±0.32 | 73.68±0.62 | 86.71±0.79 | 81.14±1.32 |
| | Co-teaching+ | 86.47±0.92 | 78.93±0.74 | 85.37±0.47 | 63.17±3.48 | 84.01±1.01 | 70.17±1.37 | 85.92±0.26 | 57.95±3.17 |
| | S2E | 90.26±0.24 | 75.20±2.05 | 90.73±0.32 | 87.83±0.97 | 89.92±0.37 | 76.18±1.93 | 90.32±0.21 | 68.93±1.86 |
| | Forward | 88.36±0.34 | 86.47±0.98 | 89.30±0.71 | 85.33±1.48 | 87.62±0.24 | 83.23±1.30 | 85.39±0.23 | 76.88±1.26 |
| | T-Revision | 89.43±0.62 | 86.98±0.87 | 89.94±0.74 | 88.11±1.22 | 91.01±0.29 | 87.10±1.38 | 90.43±0.38 | 85.46±1.04 |
| | Joint | 89.94±0.25 | 87.17±0.35 | 90.83±0.18 | 88.24±0.79 | 91.31±0.73 | 85.62±1.75 | 90.13±0.34 | 85.23±0.74 |
| | CDR | 90.26±0.31 | 87.19±0.43 | 92.00±0.27 | 88.68±0.67 | 92.11±0.23 | 88.58±0.39 | 91.14±0.23 | 86.25±0.57 |
| CIFAR-100 | CE | 63.93±0.72 | 56.82±0.82 | 64.12±0.54 | 52.86±0.92 | 64.10±0.46 | 52.77±0.79 | 63.33±0.29 | 50.84±0.89 |
| | GCE | 65.62±0.82 | 57.97±1.21 | 65.34±0.64 | 54.35±1.28 | 62.32±1.04 | 55.03±1.25 | 66.67±0.40 | 55.14±1.77 |
| | DMI | 62.77±0.92 | 57.42±0.53 | 64.30±0.84 | 51.31±2.73 | 58.77±0.64 | 42.89±0.77 | 59.04±0.35 | 46.99±0.62 |
| | APL | 59.37±0.82 | 51.03±1.04 | 54.31±0.84 | 48.22±1.35 | 59.77±0.74 | 53.25±0.92 | 49.17±2.72 | 38.18±4.04 |
| | MentorNet | 57.27±1.32 | 49.01±2.09 | 54.10±0.92 | 33.21±1.82 | 54.73±1.26 | 45.31±2.93 | 50.02±0.73 | 36.27±1.64 |
| | Co-teaching | 61.47±0.41 | 53.44±0.40 | 57.35±0.82 | 37.62±1.77 | 58.11±0.47 | 48.46±0.64 | 57.73±0.37 | 43.28±0.55 |
| | Co-teaching+ | 64.13±0.32 | 55.92±0.81 | 58.97±1.19 | 40.16±2.74 | 56.31±0.41 | 38.03±0.55 | 55.45±0.57 | 41.11±1.32 |
| | S2E | 64.21±0.72 | 43.12±2.77 | 63.92±0.46 | 42.45±1.73 | 58.21±0.43 | 41.74±2.09 | 61.08±0.59 | 47.06±1.93 |
| | Forward | 54.88±0.92 | 45.64±1.77 | 64.07±1.02 | 53.84±2.71 | 58.37±0.56 | 39.82±0.73 | 58.55±0.31 | 46.42±0.95 |
| | T-Revision | 64.67±0.38 | 57.15±1.02 | 68.02±0.53 | 54.93±1.09 | 62.69±0.73 | 52.31±1.46 | 60.22±0.68 | 50.23±1.79 |
| | Joint | 66.12±0.42 | 59.45±0.68 | 68.29±0.25 | 55.53±0.47 | 67.35±0.31 | 52.22±1.85 | 65.91±0.43 | 55.09±0.93 |
| | CDR | 68.68±0.33 | 62.72±0.38 | 70.64±0.51 | 55.58±0.78 | 71.93±0.57 | 56.94±1.30 | 69.82±0.42 | 61.03±0.77 |

Table 3: Classification accuracy (percentage) on *Food-101* dataset. The best result is in bold.

| CE | GCE | DMI | APL | MentorNet | Co-teaching |
|--------------|-------|---------|------------|-----------|--------------|
| 84.03 | 84.96 | 85.52 | 82.17 | 81.25 | 83.73 |
| Co-teaching+ | S2E | Forward | T-Revision | Joint | CDR |
| 76.89 | 84.97 | 85.52 | 85.97 | 83.10 | 86.36 |

Table 4: Top-1 validation accuracies (percentage) on clean *ILSVRC12* validation set of Inception-ResNet v2 models trained on *WebVision* dataset, under the “Mini” setting in (Jiang et al., 2018; Chen et al., 2019; Ma et al., 2020). The best result is in bold.

| CE | GCE | DMI | APL | MentorNet | Co-teaching |
|--------------|-------|---------|------------|-----------|--------------|
| 57.34 | 55.62 | 56.93 | 61.27 | 57.66 | 61.22 |
| Co-teaching+ | S2E | Forward | T-Revision | Joint | CDR |
| 33.26 | 54.33 | 56.39 | 60.58 | 47.60 | 61.85 |

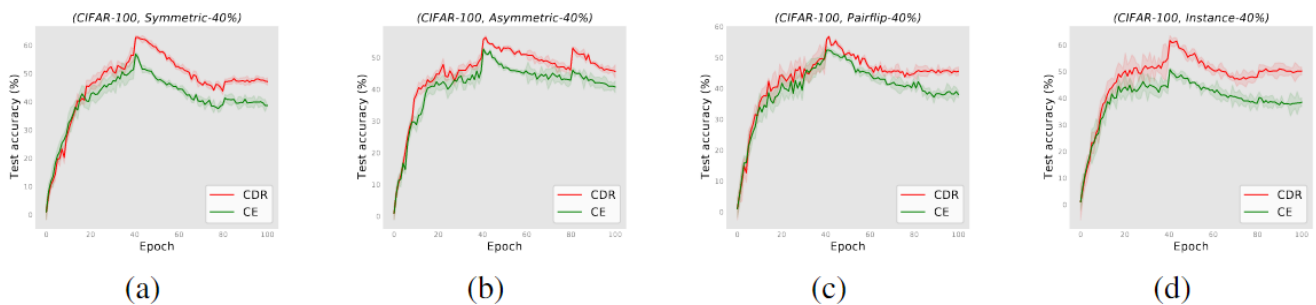
测试如何估计划分系数(默认为 $(1 - \tau)$)

Table 2: The located constant on synthetic noisy datasets with different noise levels. The result with an underline means that the located constant and the noise rate are numerically equal.

| Dataset | Symmetric | | Asymmetric | | Pairflip | | Instance | |
|-----------------|-------------|-------------|-------------|-------------|-------------|------|-------------|-------------|
| | 20% | 40% | 20% | 40% | 20% | 40% | 20% | 40% |
| <i>MNIST</i> | <u>0.20</u> | 0.50 | <u>0.20</u> | <u>0.40</u> | <u>0.20</u> | 0.50 | 0.30 | 0.60 |
| <i>F-MNIST</i> | <u>0.20</u> | <u>0.40</u> | <u>0.20</u> | 0.50 | 0.30 | 0.50 | <u>0.20</u> | 0.60 |
| <i>CIFAR-10</i> | 0.30 | 0.50 | 0.30 | 0.30 | 0.30 | 0.50 | <u>0.20</u> | <u>0.40</u> |

在同一数据集上找出最好的划分系数与 $(1-\tau)$ 作比较

t%e



证明在 early training stage时这种方法确实可以增强泛化性