

# Few-Shot Class-Incremental Learning from an Open-Set Perspective

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## 1 Introduction

In the supplementary material, we present more details about the experiments in our paper. The detailed average accuracy and harmonic accuracy values are reported in the tables. Following the CEC paper [7], we also report on the performance dropping rate (PD). The PD measures the absolute accuracy decrease between the base learning and the last incremental session.

## 2 Detailed Results

Table 1: Experimental results for the *8-step 5-way 5-shot* FSCIL protocol on the CIFAR100 dataset. The performance dropping rate (PD) measures the absolute accuracy decrease between the base learning and the last incremental session. The \* indicates results reported in [7,6] and the ‡ indicates results from our implementation using the official published code.

	0	1	2	3	4	5	6	7	8	PD ↓
class-wise average accuracy										
Ft-CNN*	64.1	36.9	15.4	9.8	6.7	3.8	3.7	3.1	2.7	61.4
iCaRL* [5]	64.1	53.3	41.7	34.1	27.9	25.1	20.4	15.5	13.7	50.4
EEIL* [1]	64.1	53.1	43.7	35.2	29.0	25.0	21.0	17.3	15.9	48.2
NCM* [4]	64.1	53.1	44.0	37.0	31.6	26.7	21.2	16.8	13.5	50.6
TOPIC* [6]	64.1	55.9	47.1	45.2	40.1	36.4	34.0	31.6	29.4	34.7
CEC* [7]	73.1	68.9	65.3	61.2	58.1	55.6	53.2	51.3	49.1	<b>24.0</b>
CEC‡ [7]	74.0	68.1	64.2	60.6	57.3	54.8	52.5	50.3	48.1	25.9
ALICE (Ours)	<b>79.0</b>	<b>70.5</b>	<b>67.1</b>	<b>63.4</b>	<b>61.2</b>	<b>59.2</b>	<b>58.1</b>	<b>56.3</b>	<b>54.1</b>	24.9
harmonic accuracy										
CEC‡ [7]	-	40.2	37.6	34.9	32.9	33.6	33.1	31.9	31.3	-
ALICE (Ours)	-	<b>65.3</b>	<b>62.3</b>	<b>55.7</b>	<b>54.5</b>	<b>54.0</b>	<b>53.9</b>	<b>52.1</b>	<b>50.6</b>	-

Table 2: Experimental results for the *8-step 5-way 5-shot* FSCIL protocol on the miniImageNet dataset.

	0	1	2	3	4	5	6	7	8	PD ↓
class-wise average accuracy										
Ft-CNN*	61.3	27.2	16.4	6.1	2.5	1.6	1.9	2.6	1.4	59.9
iCaRL* [5]	61.3	46.3	42.9	37.6	30.5	24.0	20.9	18.8	17.2	44.1
EEIL* [1]	61.3	46.6	44.0	37.3	33.1	27.1	24.1	21.6	19.6	41.7
NCM* [4]	61.3	47.8	39.3	31.9	25.7	21.4	18.7	17.2	14.2	47.1
TOPIC* [6]	61.3	50.1	45.2	41.2	37.5	35.5	32.2	29.5	24.4	36.9
CEC* [7]	72.0	66.8	63.0	59.4	56.7	53.7	51.2	49.2	47.6	24.4
CEC‡ [7]	71.2	66.0	61.9	58.6	56.4	53.4	50.7	48.8	47.2	<b>24.0</b>
ALICE (Ours)	<b>80.6</b>	<b>70.6</b>	<b>67.4</b>	<b>64.5</b>	<b>62.5</b>	<b>60.0</b>	<b>57.8</b>	<b>56.8</b>	<b>55.7</b>	24.9
harmonic accuracy										
CEC‡ [7]	-	34.6	31.0	29.0	31.8	28.9	26.9	27.5	28.1	-
ALICE (Ours)	-	<b>64.9</b>	<b>58.9</b>	<b>56.4</b>	<b>55.4</b>	<b>52.7</b>	<b>50.8</b>	<b>51.0</b>	<b>50.9</b>	-

Table 3: Experimental results for the *10-step 10-way 5-shot* FSCIL protocol on the CUB200 dataset.

	0	1	2	3	4	5	6	7	8	9	10	PD ↓
class-wise average accuracy												
Ft-CNN*	68.7	43.7	25.1	17.7	18.1	17.0	15.1	10.6	8.9	8.9	8.5	60.2
iCaRL* [5]	68.7	52.7	48.6	44.2	36.6	29.5	27.8	26.3	24.0	23.9	21.2	47.5
EEIL* [1]	68.7	53.6	47.9	44.2	36.3	27.5	25.9	24.7	24.0	24.1	22.1	46.6
NCM* [4]	68.7	57.1	44.2	28.8	26.7	25.7	24.6	21.5	20.1	20.1	19.9	48.8
TOPIC* [6]	68.7	62.5	54.8	50.0	45.3	41.4	38.4	35.4	32.2	28.3	26.3	42.4
Cheraghian <i>et al.</i> [2]	68.2	60.5	55.7	50.5	45.7	42.9	40.9	38.8	36.5	34.9	33.0	35.2
Cheraghian <i>et al.</i> [3]	68.8	59.4	59.3	55.0	52.6	49.8	48.1	46.3	44.3	43.4	43.2	25.6
CEC [7]	75.9	71.9	68.5	63.5	62.4	58.3	57.7	55.8	54.8	53.5	52.3	23.6
CEC‡ [7]	75.0	71.3	67.3	63.5	61.5	58.3	56.3	54.5	52.2	51.9	50.7	24.3
ALICE (Ours)	<b>77.4</b>	<b>72.7</b>	<b>70.6</b>	<b>67.2</b>	<b>65.9</b>	<b>63.4</b>	<b>62.9</b>	<b>61.9</b>	<b>60.5</b>	<b>60.6</b>	<b>60.1</b>	<b>17.3</b>
harmonic accuracy												
CEC‡ [7]	-	59.6	52.6	46.6	48.1	45.0	44.7	44.4	42.3	44.2	43.9	-
ALICE (Ours)	-	<b>70.0</b>	<b>65.6</b>	<b>59.3</b>	<b>59.6</b>	<b>57.6</b>	<b>58.9</b>	<b>58.8</b>	<b>57.8</b>	<b>58.8</b>	<b>59.0</b>	-

Table 4: Experimental results for the *8-step 5-way 1-shot* FSCIL protocol on the CIFAR100 dataset.

	0	1	2	3	4	5	6	7	8	PD ↓
class-wise average accuracy										
CEC <sup>‡</sup> [7]	74.0	67.3	62.6	59.0	55.3	52.1	49.5	47.0	44.8	<b>29.2</b>
ALICE (Ours)	<b>79.0</b>	<b>71.0</b>	<b>66.4</b>	<b>62.2</b>	<b>58.1</b>	<b>54.7</b>	<b>52.0</b>	<b>49.8</b>	<b>47.5</b>	31.5
harmonic accuracy										
CEC <sup>‡</sup> [7]	-	12.1	11.4	14.3	13.4	13.1	13.7	13.3	13.0	-
ALICE (Ours)	-	<b>35.7</b>	<b>33.9</b>	<b>33.0</b>	<b>29.2</b>	<b>28.2</b>	<b>27.6</b>	<b>27.3</b>	<b>26.5</b>	-

Table 5: Experimental results for the *8-step 5-way 1-shot* FSCIL protocol on the miniImageNet dataset.

	0	1	2	3	4	5	6	7	8	PD ↓
class-wise average accuracy										
CEC <sup>‡</sup> [7]	71.2	66.3	61.6	57.6	54.0	50.8	48.2	45.9	43.7	<b>27.5</b>
ALICE (Ours)	<b>80.6</b>	<b>70.7</b>	<b>65.8</b>	<b>61.8</b>	<b>58.4</b>	<b>55.3</b>	<b>52.4</b>	<b>50.7</b>	<b>48.6</b>	32.0
harmonic accuracy										
CEC <sup>‡</sup> [7]	-	9.0	7.9	7.3	6.7	6.0	6.4	7.2	7.8	-
ALICE (Ours)	-	<b>35.2</b>	<b>25.2</b>	<b>24.5</b>	<b>26.0</b>	<b>25.3</b>	<b>23.9</b>	<b>26.8</b>	<b>27.1</b>	-

Table 6: Experimental results for the *10-step 10-way 1-shot* FSCIL protocol on the CUB200 dataset.

	0	1	2	3	4	5	6	7	8	9	10	PD ↓
class-wise average accuracy												
CEC <sup>‡</sup> [7]	75.0	<b>69.5</b>	<b>64.9</b>	<b>59.9</b>	<b>57.0</b>	<b>53.1</b>	50.7	48.0	46.0	44.8	43.0	32.0
ALICE (Ours)	<b>77.4</b>	66.7	62.7	58.6	55.3	<b>53.1</b>	<b>50.9</b>	<b>49.3</b>	<b>47.1</b>	<b>46.9</b>	<b>45.7</b>	<b>31.7</b>
harmonic accuracy												
CEC <sup>‡</sup> [7]	-	32.5	31.8	24.8	27.2	25.5	25.4	24.5	24.3	26.0	25.5	-
ALICE (Ours)	-	<b>40.8</b>	<b>38.4</b>	<b>33.4</b>	<b>33.0</b>	<b>33.9</b>	<b>33.8</b>	<b>34.9</b>	<b>33.2</b>	<b>36.3</b>	<b>36.3</b>	-

## References

1. Castro, F.M., Marín-Jiménez, M.J., Guil, N., Schmid, C., Alahari, K.: End-to-end incremental learning. In: Proceedings of the European Conference on Computer Vision (ECCV). pp. 233–248 (2018)
2. Cheraghian, A., Rahman, S., Fang, P., Roy, S.K., Petersson, L., Harandi, M.: Semantic-aware knowledge distillation for few-shot class-incremental learning. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 2534–2543 (2021)
3. Cheraghian, A., Rahman, S., Ramasinghe, S., Fang, P., Simon, C., Petersson, L., Harandi, M.: Synthesized feature based few-shot class-incremental learning on a mixture of subspaces. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 8661–8670 (2021)
4. Hou, S., Pan, X., Loy, C.C., Wang, Z., Lin, D.: Learning a unified classifier incrementally via rebalancing. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 831–839 (2019)
5. Rebuffi, S.A., Kolesnikov, A., Sperl, G., Lampert, C.H.: icarl: Incremental classifier and representation learning. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 2001–2010 (2017)
6. Tao, X., Hong, X., Chang, X., Dong, S., Wei, X., Gong, Y.: Few-shot class-incremental learning. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 12183–12192 (2020)
7. Zhang, C., Song, N., Lin, G., Zheng, Y., Pan, P., Xu, Y.: Few-shot incremental learning with continually evolved classifiers. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 12455–12464 (2021)