6th CLVISION ICCV Workshop

ICCV HONOLULU HAWAII OCT 19-23, 2025

Does Prior Data Matter? Exploring Joint Training in the Context of Few-Shot Class-Incremental Learning

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Introduction

I. Background

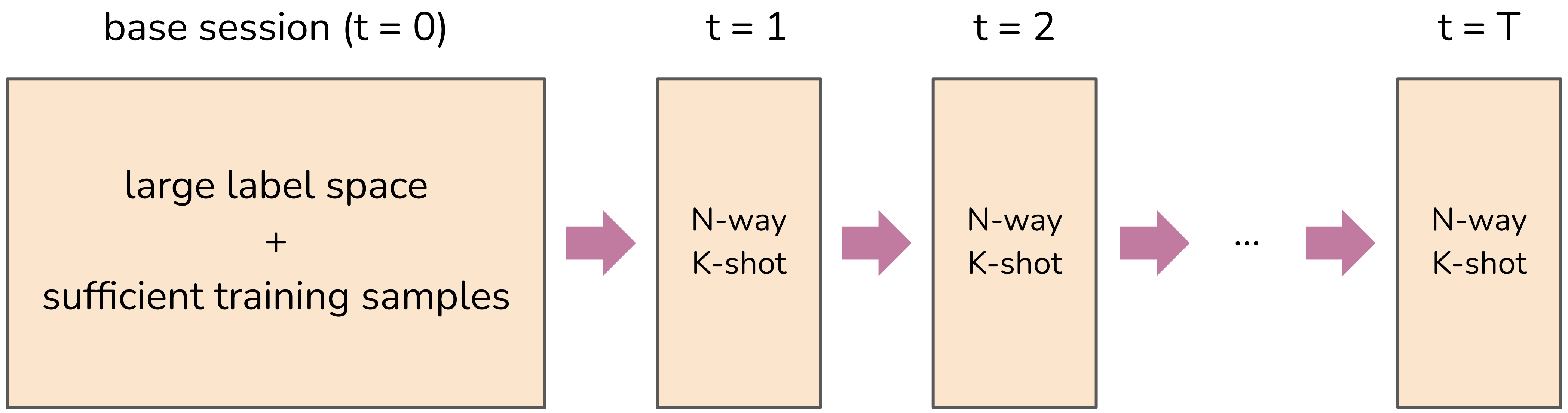
Deep neural networks (DNNs) face the challenge of ***catastrophic forgetting*** when trained on streaming data

Class-Incremental Learning (CIL)

Adapt to new classes over time + Maintain strong performance on all previously observed classes

Few-Shot Class-Incremental Learning (FSCIL)

New classes emerge with only a few samples



Introduction

II. Motivation

Fundamental assumption in FSCIL:
"Previously seen data are no longer accessible in the following incremental sessions"

However, in many real-world scenarios such as e-commerce applications or industrial deployments, **previously collected datasets often remain available.**

"If previous data is accessible, is it better to retrain a model using all accumulated data (i.e., joint training), or to update the model solely based on the newly introduced data (i.e., incremental learning)?"

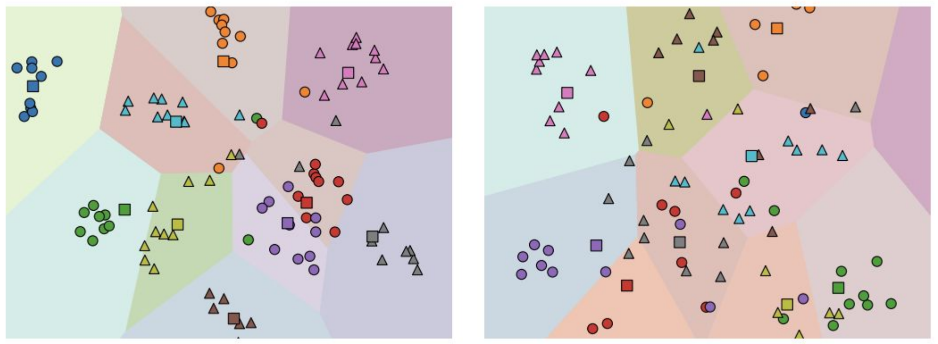
CIL

- Joint training is widely regarded as the ideal upper bound.
- A well-defined upper bound provides a practical guideline:

"When access to previous data is permitted, joint training is preferred for maximizing performance, whereas CIL methods are viable alternatives under constraints in training time or computational resources."

FSCIL

- Joint training is less effective in FSCIL due to class imbalance.



(a) Joint training in CIL setting (b) Joint training in FSCIL setting

"It remains unclear whether retraining on the full dataset or incremental learning is preferable in FSCIL scenarios."

Introduction

III. Contributions

To the best of our knowledge, no prior work has investigated how to effectively leverage past data in FSCIL settings. However, there remains a question on the ***"practical impact of full data access on model performance."***

Our contributions:

1. **Develop a more realistic joint training benchmark** for comparison with FSCIL approaches.
    - Explore 8 imbalanced learning techniques and identify/evaluate the optimal combination.
    - Present this combination as a new imbalance-aware joint training benchmark for FSCIL.

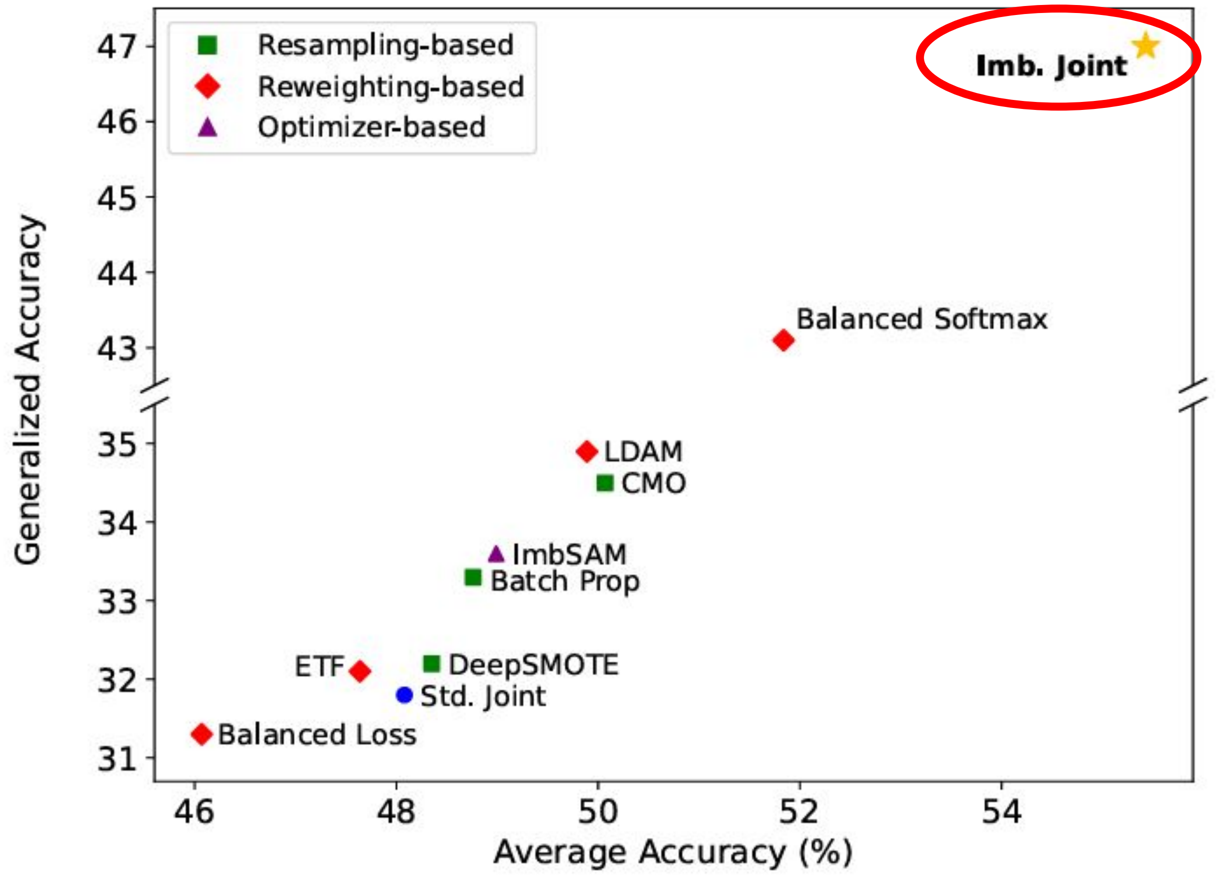
2. **Provide practical insights and guidelines** for selecting suitable training strategies in FSCIL scenarios.
    - Compare the new benchmark with state-of-the-art FSCIL methods under varying resource constraints.
    - Reimplement and integrate all methods into a unified framework to ensure fair and consistent comparison.

Rethinking Joint Training in FSCIL

I. Imbalance-Aware Joint Training in FSCIL

Exploring *imbalanced learning* strategies

- We explore three independent categories of imbalanced learning:
  - 3 Resampling-based methods
  - 4 Reweighting-based methods
  - 1 Optimizer-based method
- Combining CMO, Balanced Softmax, and ImbSAM achieves the best overall performance.



Ablation Study

- The new imbalance-aware joint training benchmark **<u>improves</u>** *aAcc* by 7%p and *gAcc* by 15%p over standard joint training.

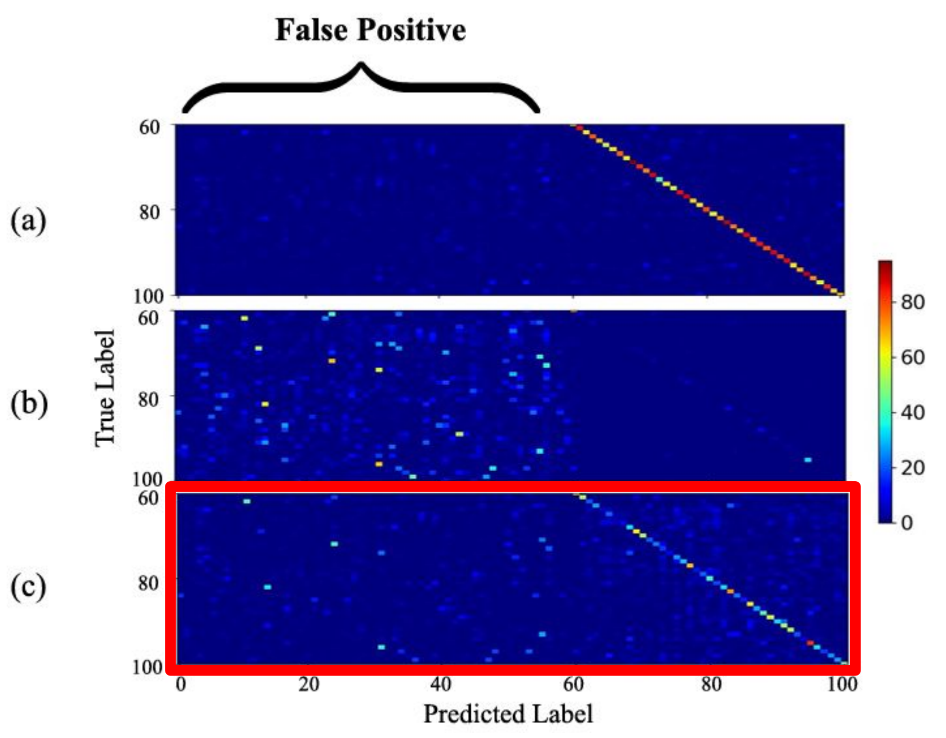
CMO	*BalancedSoftmax*	*ImbSAM*	*aAcc*	*gAcc*
			48.1	31.8
✓			50.1	34.5
✓	✓		55.5	45.9
✓	✓	✓	**55.8**	**46.8**

Rethinking Joint Training in FSCIL

II. Analysis of Imbalance-Aware Joint Training

Resolving bias towards base classes

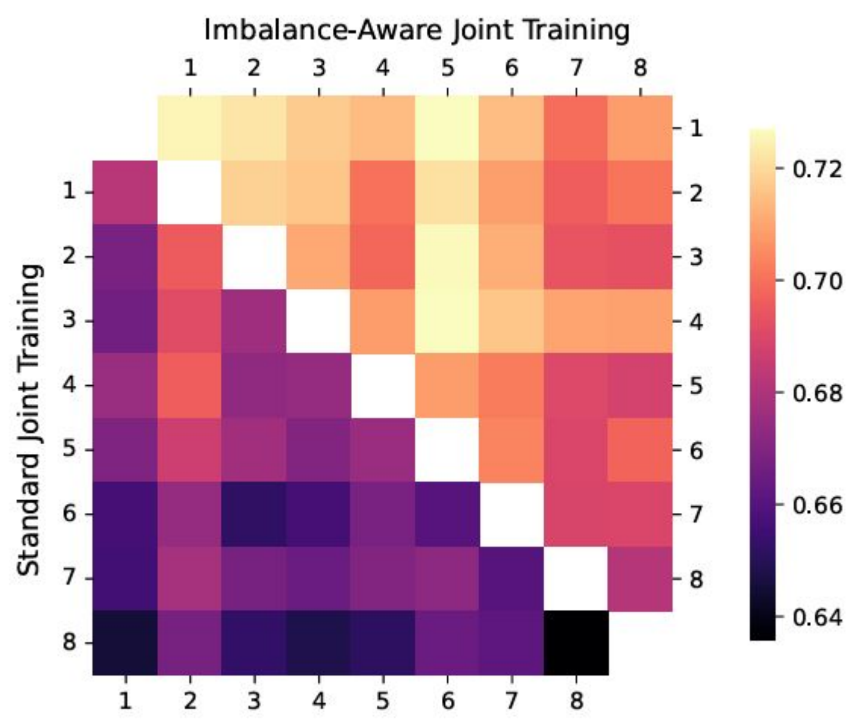
- Comparison of ***confusion matrices***:
  - (a) standard joint training in CIL
  - (b) standard joint training in FSCIL
  - (c) imbalance-aware joint training in FSCIL



*(c) shows **fewer FPs for incremental classes** than (b), suggesting a more reliable benchmark for FSCIL.*

Resemblance to joint training in CIL

- ***Centered Kernel Alignment (CKA)*** feature similarity vs. standard joint training in CIL:
  - (a) Upper: imbalance-aware joint training in FSCIL
  - (b) Lower: standard joint training in FSCIL



*(a) exhibits brighter coloration than (b), indicating **stronger feature similarity** to standard joint training in CIL.*

Towards a Practical Guideline for FSCIL

I. Experimental Setup

General settings

- **Dataset:** CIFAR-100, *mini*ImageNet, and CUB-200
- **Evaluation metrics:** average accuracy (aAcc) and generalized average accuracy (gAcc)

A standardized evaluation protocol for FSCIL

1) **Exposure of test set during training:**
   - Many methods select the best-performing base session epoch using the test set.
   - Some methods use the test set from the last session for hyperparameter tuning.

   ➡ **We create a new validation set by splitting the original training set in a 9:1 ratio.**

2) **Unfair usage of pre-trained encoders:**
   - The *YourSelf* method leverages additional information from a pre-trained encoder.

   ➡ **We restrict this method to rely solely on a model trained under our evaluation protocol.**

		CEC	S3C	WaRP	FACT	TEEN	SAVC	LIMIT	Yourself
1)	**P1**: Exposure of test set during training	✓	✓	✗	✗	✓	✓	✓	✗
2)	**P2**: Unfair usage of pre-trained encoders	✗	✗	✗	✗	✗	✗	✗	✓

Towards a Practical Guideline for FSCIL

II. Comparison of FSCIL and Joint Training

← **Joint training outperforms FSCIL** | → **FSCIL outperforms Joint training**

Method	S8	*aAcc* S8 Base	*aAcc* S8 Inc.	*aAcc*	*gAcc*
Std. Joint	48.1	**78.8**	1.9	61.1	46.9
Imb. Joint	**55.3**	70.5	32.5	**65.9**	**58.0**
CEC [55]	39.7	50.5	23.5	50.5	45.9
FACT [60]	42.4	62.5	12.1	53.1	43.6
TEEN [48]	41.7	63.7	8.8	52.6	42.4
S3C [23]	41.3	47.4	32.1	48.4	45.5
WaRP [25]	47.1	64.2	21.6	57.0	49.2
SAVC [39]	54.7	76.5	22.2	65.8	55.6
LIMIT [61]	49.7	68.9	21.1	60.4	51.2
YourSelf [40]	48.5	56.0	**37.3**	58.7	54.6

Results on CIFAR-100

Method	S8	*aAcc* S8 Base	*aAcc* S8 Inc.	*aAcc*	*gAcc*
Std. Joint	44.2	72.3	2.1	56.0	43.0
Imb. Joint	51.7	66.7	29.1	60.6	53.5
CEC [55]	46.7	65.2	18.9	56.5	47.9
FACT [60]	44.1	66.8	9.9	54.9	44.4
TEEN [48]	43.8	58.0	22.4	52.7	45.8
S3C [23]	40.7	51.4	24.9	47.7	42.3
WaRP [25]	49.7	65.9	25.4	58.6	50.8
SAVC [39]	**54.1**	**76.2**	21.1	**65.3**	**55.6**
LIMIT [61]	47.1	64.2	21.6	57.3	49.2
YourSelf [40]	49.4	60.9	**32.2**	58.2	52.6

Results on *mini*ImageNet

Method	S10	*aAcc* S10 Base	*aAcc* S10 Inc.	*aAcc*	*gAcc*
Std. Joint	58.3	**77.4**	40.1	62.6	57.0
Imb. Joint	61.9	73.2	51.4	65.1	62.8
CEC [55]	44.6	66.2	24.1	52.2	48.1
FACT [60]	55.2	73.0	38.1	61.0	57.1
TEEN [48]	54.9	70.5	40.0	60.7	57.8
S3C [23]	49.9	54.5	44.1	52.7	52.1
WaRP [25]	56.2	72.3	40.9	61.4	57.9
SAVC [39]	59.9	75.1	45.4	64.3	60.4
LIMIT [61]	40.3	58.1	23.3	48.2	44.2
YourSelf [40]	**62.5**	73.4	**52.3**	**66.4**	**64.3**

Results on CUB-200

"Contrary to expectations, imbalance-aware joint training does not always outperform FSCIL methods."

- On *mini*ImageNet and CUB-200, *SAVC* and *YourSelf* achieve better performance than imbalance-aware joint training.
- This may be due to the fact that conventional imbalanced learning is not designed for **the extreme data skew in FSCIL.**

Towards a Practical Guideline for FSCIL

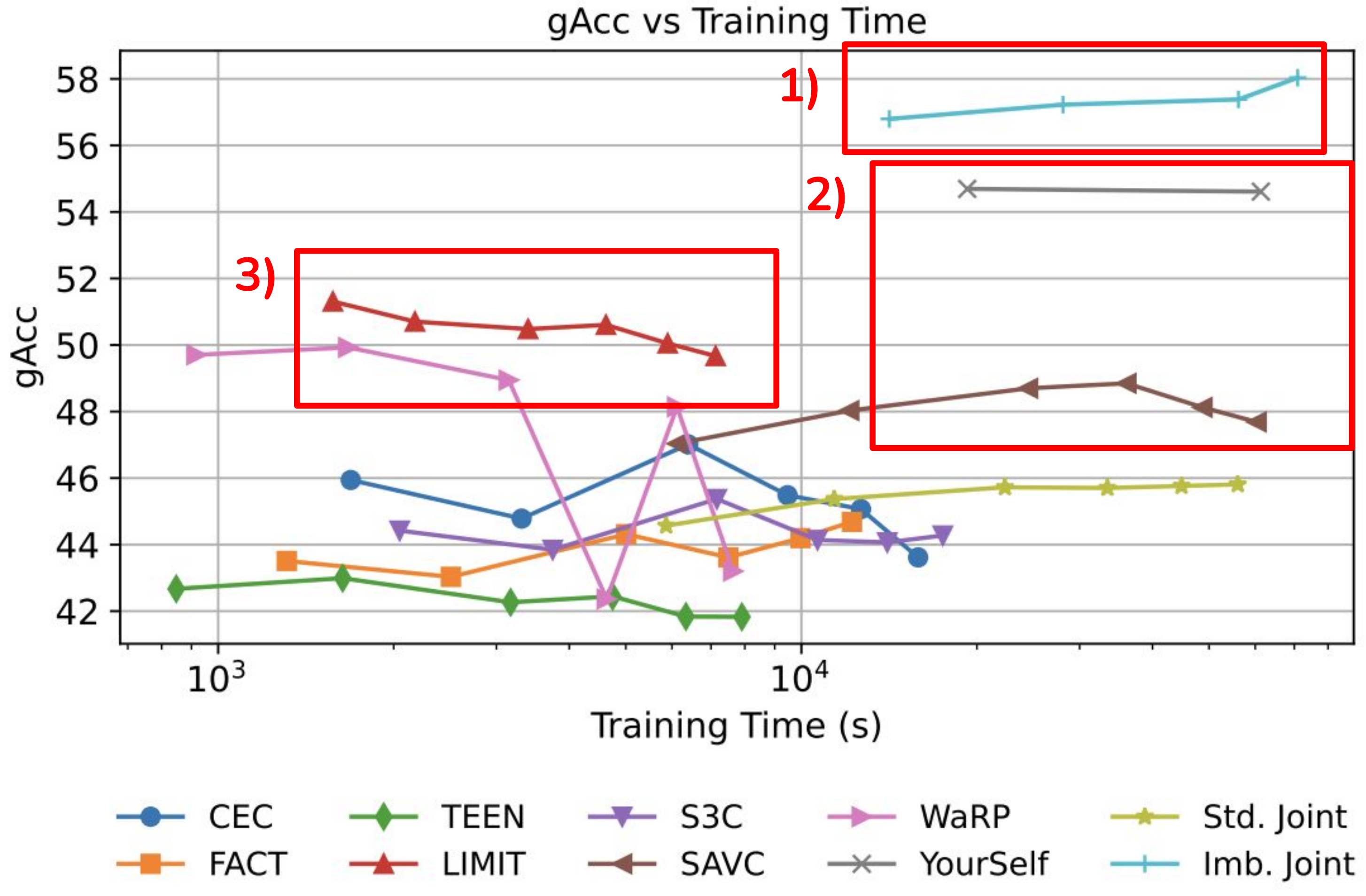
III. Resource-Aware Comparison

Under the standard training protocol, **performance trends over training time** suggest the following insights:

1) With sufficient resources and access to prior data,
imbalance-aware joint training is effective.

2) If resources are sufficient but prior data is unavailable,
***SAVC* or *YourSelf* perform well despite longer training times.**

3) When both resources and prior data are limited,
LIMIT provides the best trade-off between efficiency and performance.



Conclusion

Summary and Future Work

Key Gap:

- Lack of empirical analysis on ***the practical impact of full data access*** in the FSCIL scenario.
- Lack of ***a comparative benchmark*** to evaluate the benefits of utilizing past data.

"We suggest ***an imbalance-aware joint training benchmark*** for FSCIL and ***offer practical guidelines based on extensive comparisons*** with state-of-the-art FSCIL methods."

Future Work:

- Develop imbalanced learning approaches for data distributions as challenging as those in the FSCIL setting.
- Apply FSCIL methods to imbalanced learning tasks, leveraging their robustness to extreme data imbalance.