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Class-Domain Incremental Learning with Extensible Multi-Center Modeling

EMCift

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Classes and domains arrive in fragments

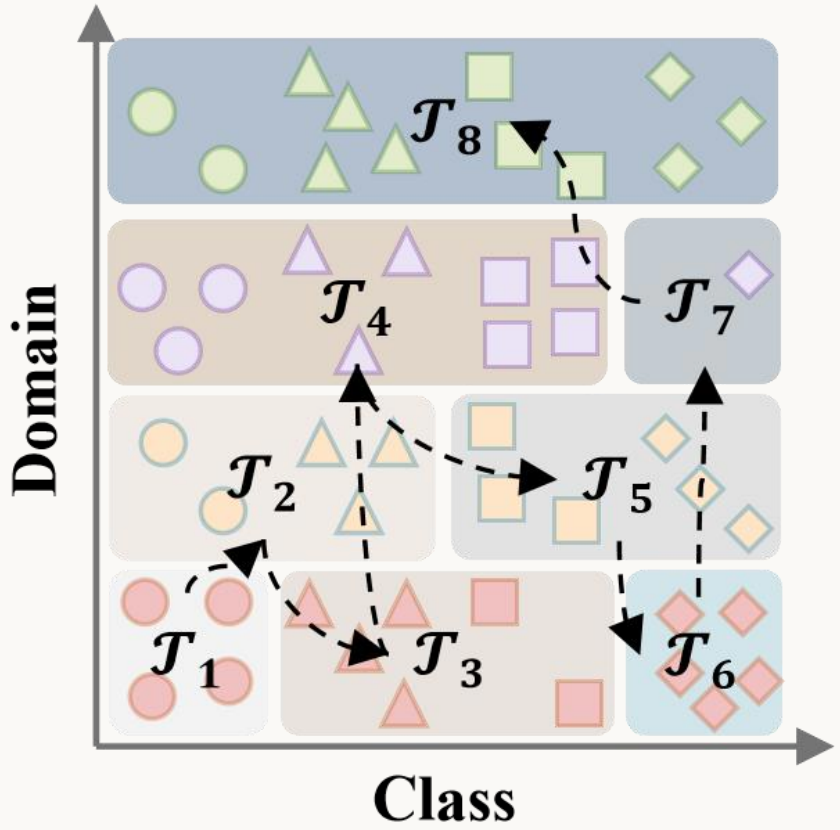
Example training stream

Task 1 Handwriting: 7

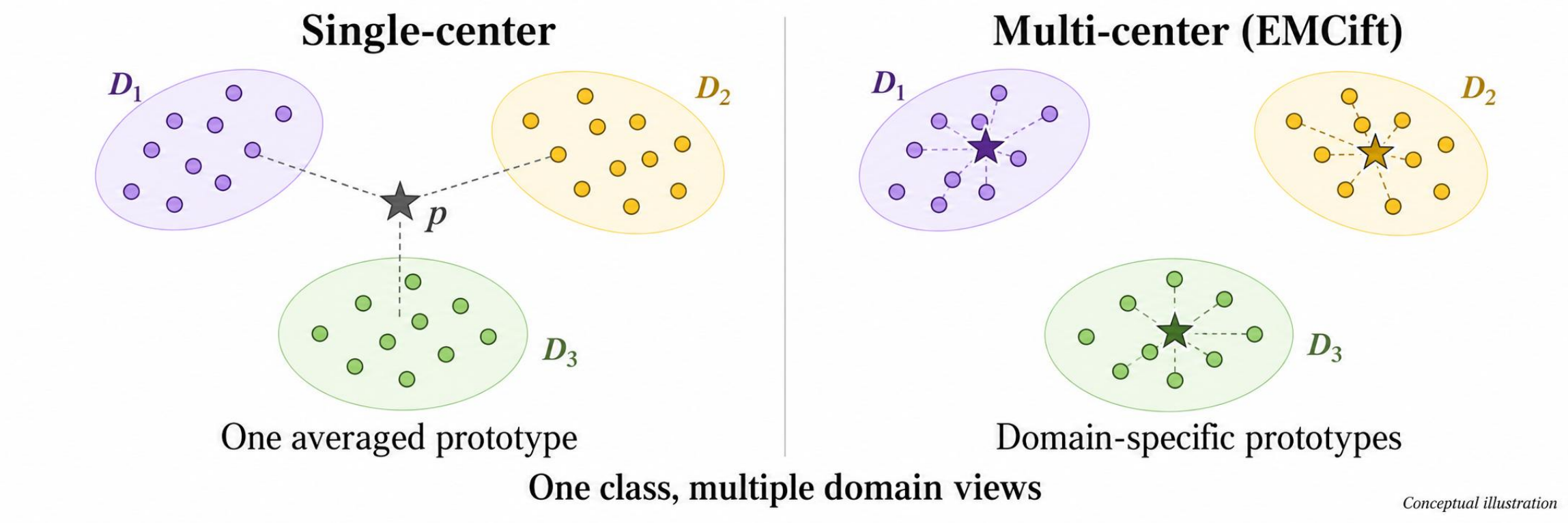
Task 2 Print: 3 and 7

Task 3 Handwriting: 9

Test time: no task or domain ID

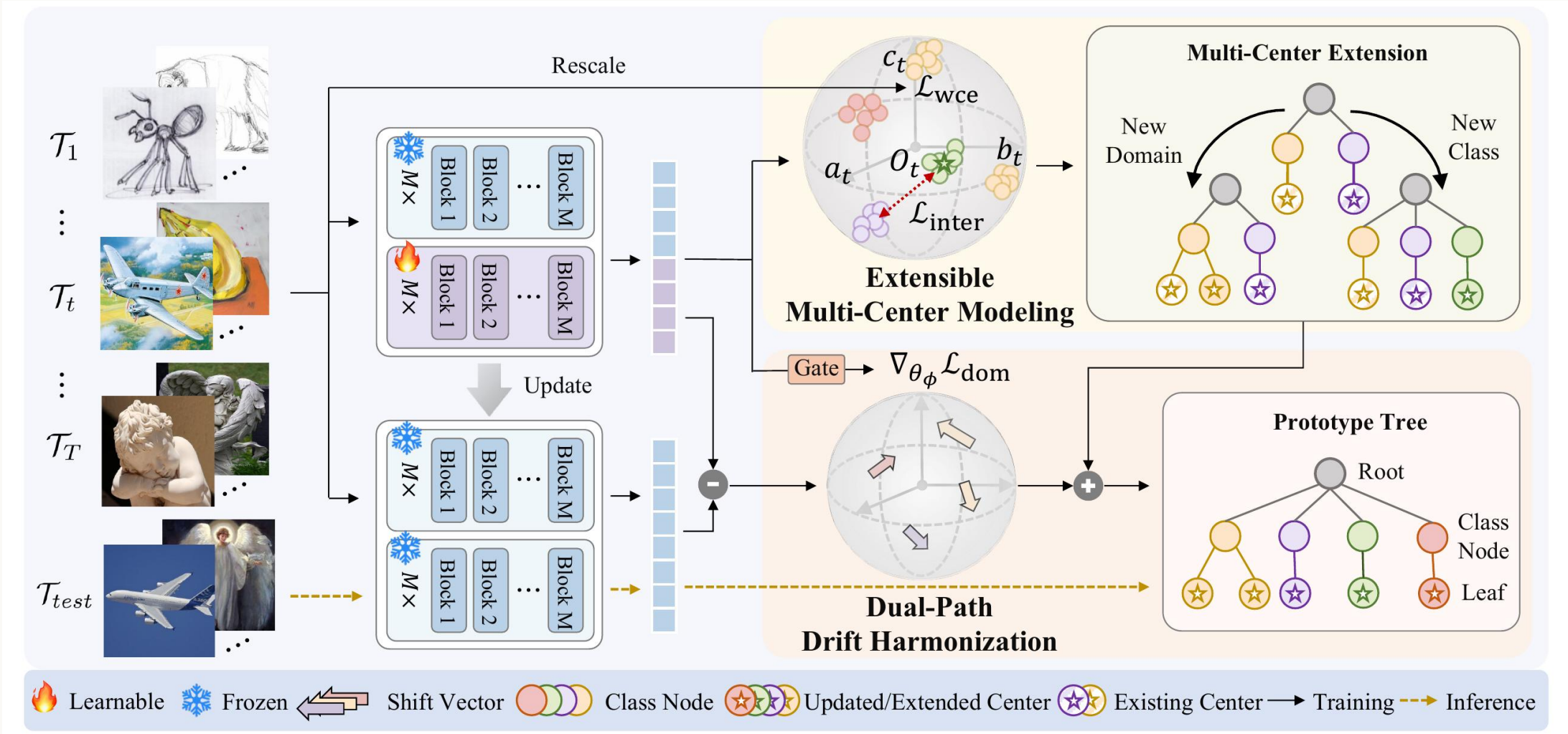


One class can have several clusters



A separate prototype preserves each observed domain view.

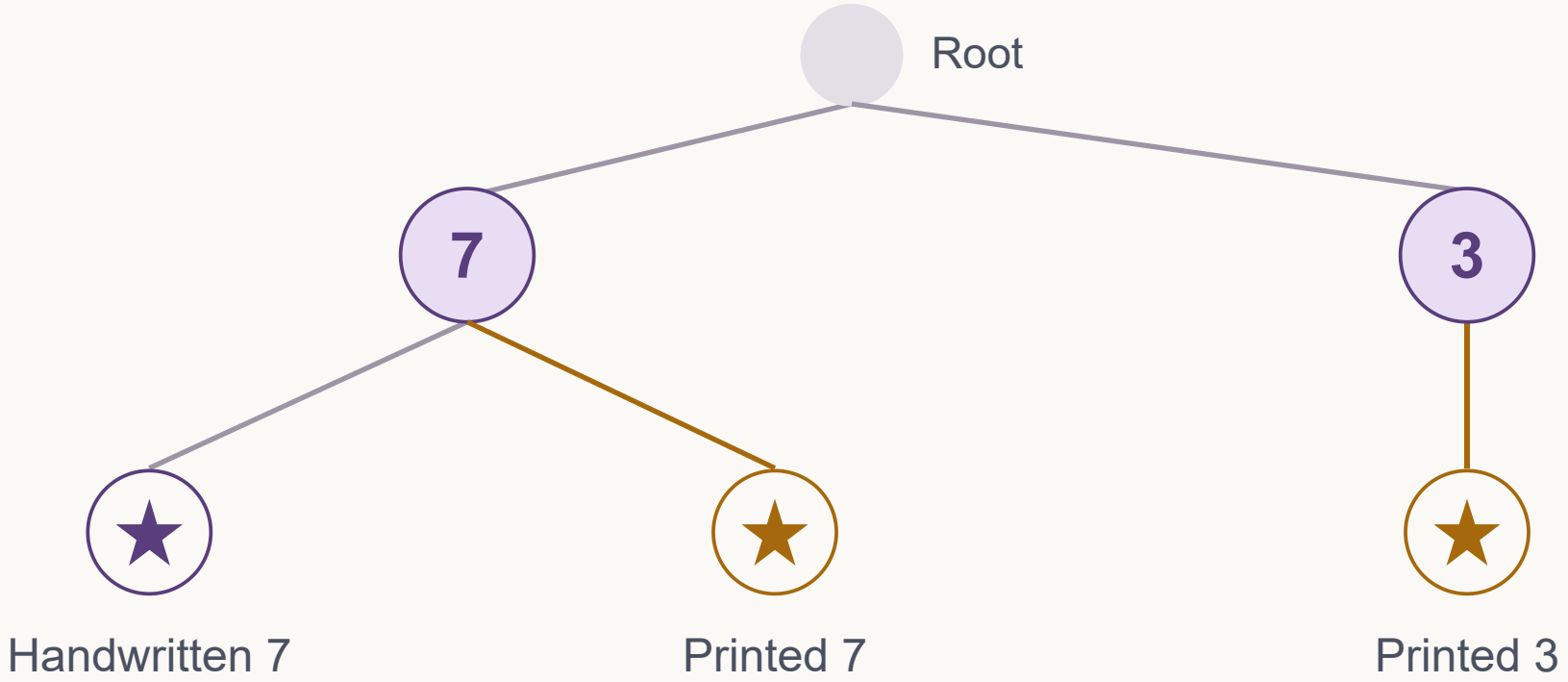
EMCift framework



Framework diagram from the paper

The prototype tree grows as views arrive

A leaf stores one class–domain prototype



Class score = best cosine match among its leaves

Different classes need room to separate

Inter-view loss

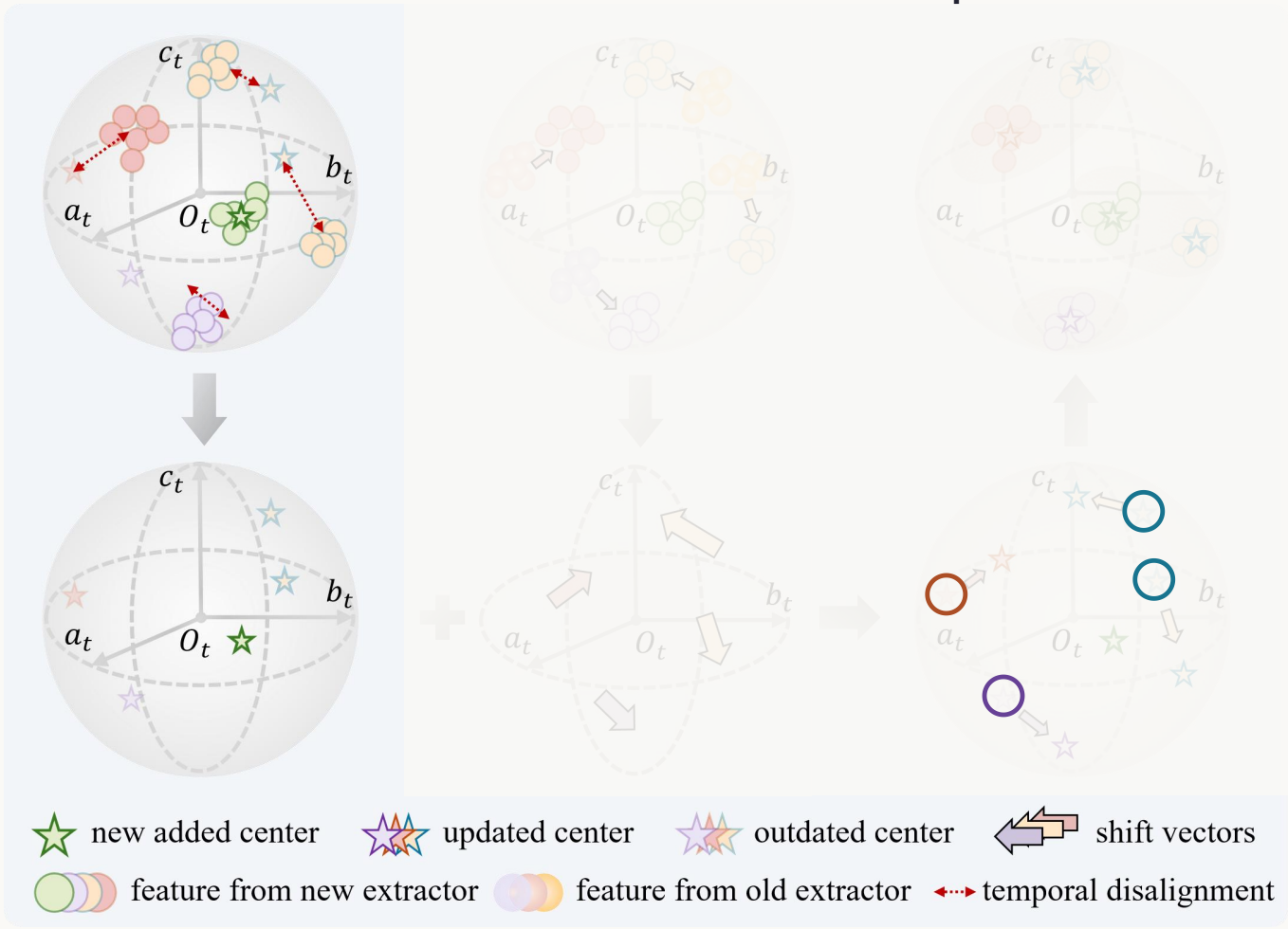
Apply a separation margin to pairs with different class labels.
Handwritten and printed 7s can keep distinct clusters.

Weighted cross-entropy

Give rare class–domain pairs more weight in training.

Two paths address feature drift

Prototype drift path



Model drift path

New domain
Alignment on

Recurring domain
Alignment off

Adversarial alignment
during training

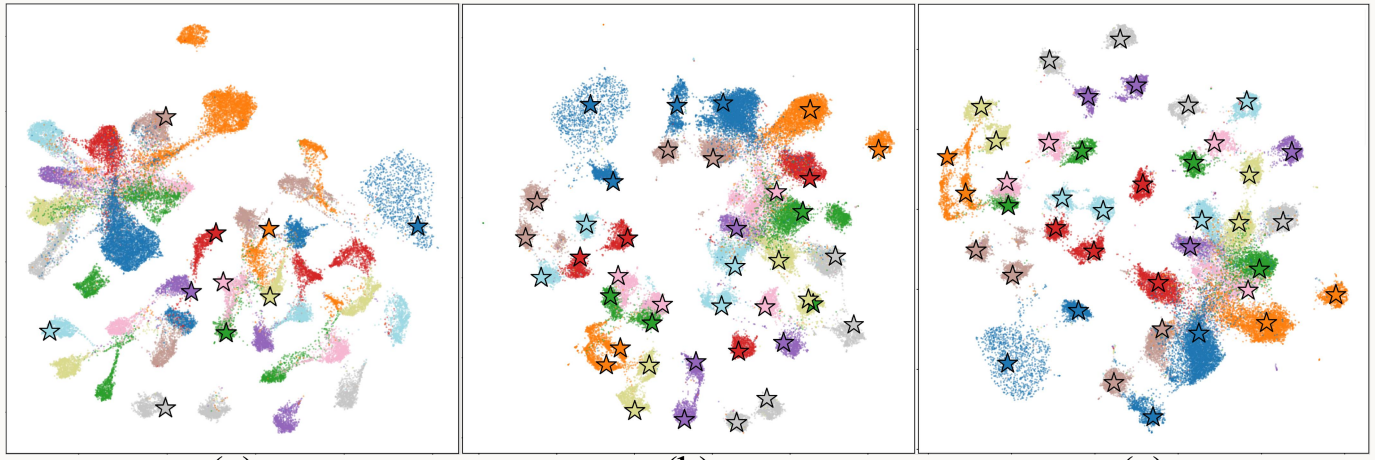
EMCift improves accuracy on all three benchmarks

Average incremental accuracy (%), mean of 3 runs

Dataset	Best baseline	EMCift	Gain
iDigits	76.13	**87.65**	**+11.52 pp**
DomainNet	61.00	**66.54**	**+5.54 pp**
CORe50	85.64	**90.69**	**+5.05 pp**

One replay exemplar per observed class–domain pair

Multiple centers and both drift paths help



(a) single center

(b) without prototype drift

(c) full EMCift

+8.90 pp

Adding multi-center modeling to the single-center variant

Accuracy drops when either drift path is removed.

Keep distinct views.
Keep old prototypes aligned.