

FORLA: Federated Object-Centric Representation Learning with Slot Attention

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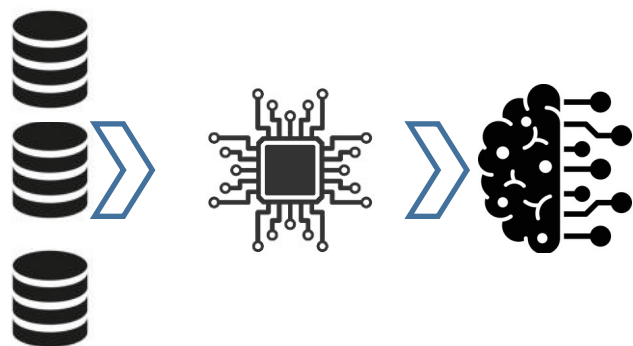
NeurIPS 2025



Motivation & Background

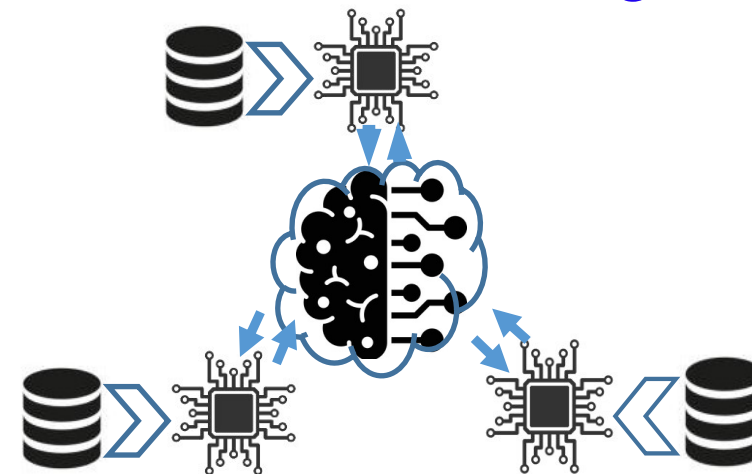


Centralized Learning



VS

Federated learning

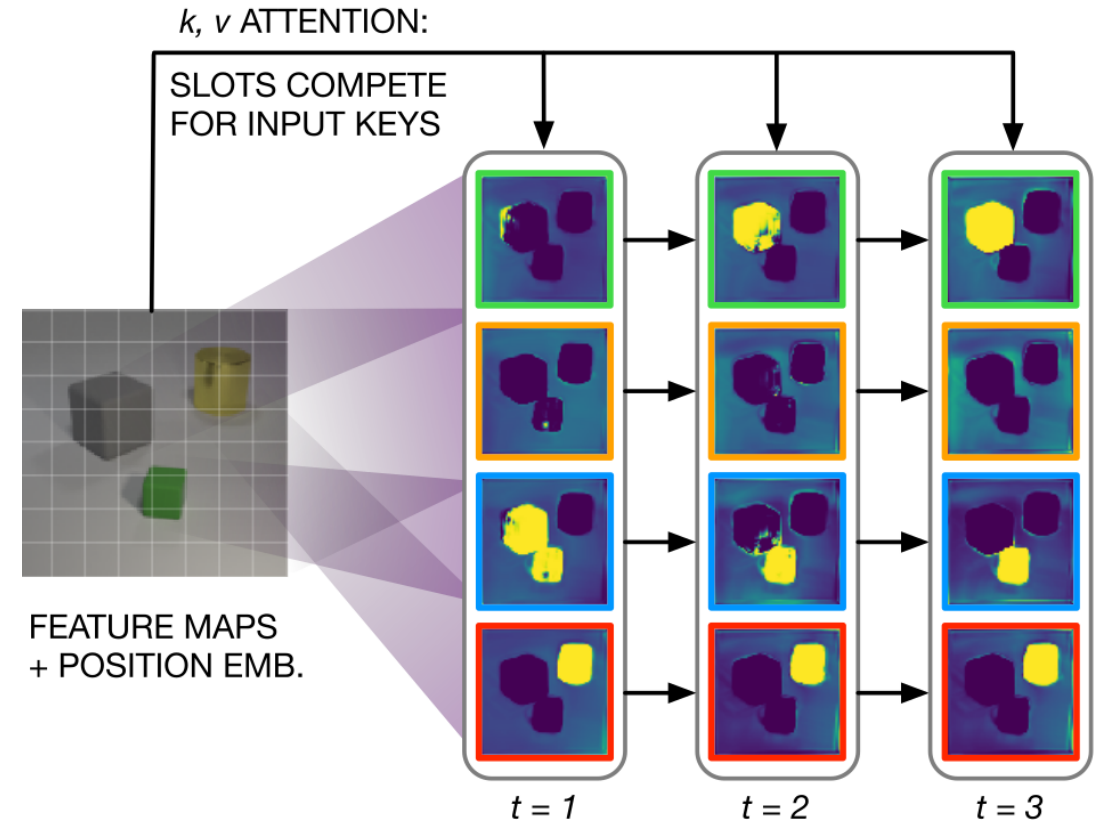


- ❑ Can we learn disentangled universal representations (foundation models) from distributed, non-IID datasets?
- Self-supervised object-centric learning offers the right inductive bias for learning semantically meaningful representations.
- Federated learning across curated datasets integrates local, object-level knowledge across clients.

Motivation & Background

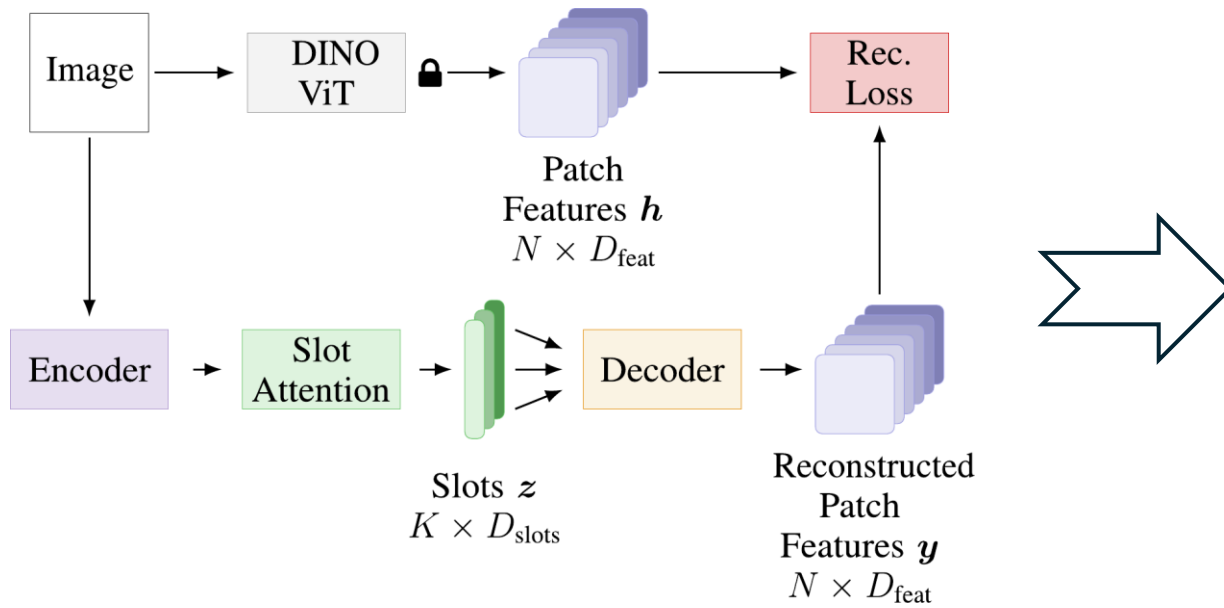


- Slot Attention model groups input pixels into slots via iterative attention
- Learning follows a reconstruction objective without labels

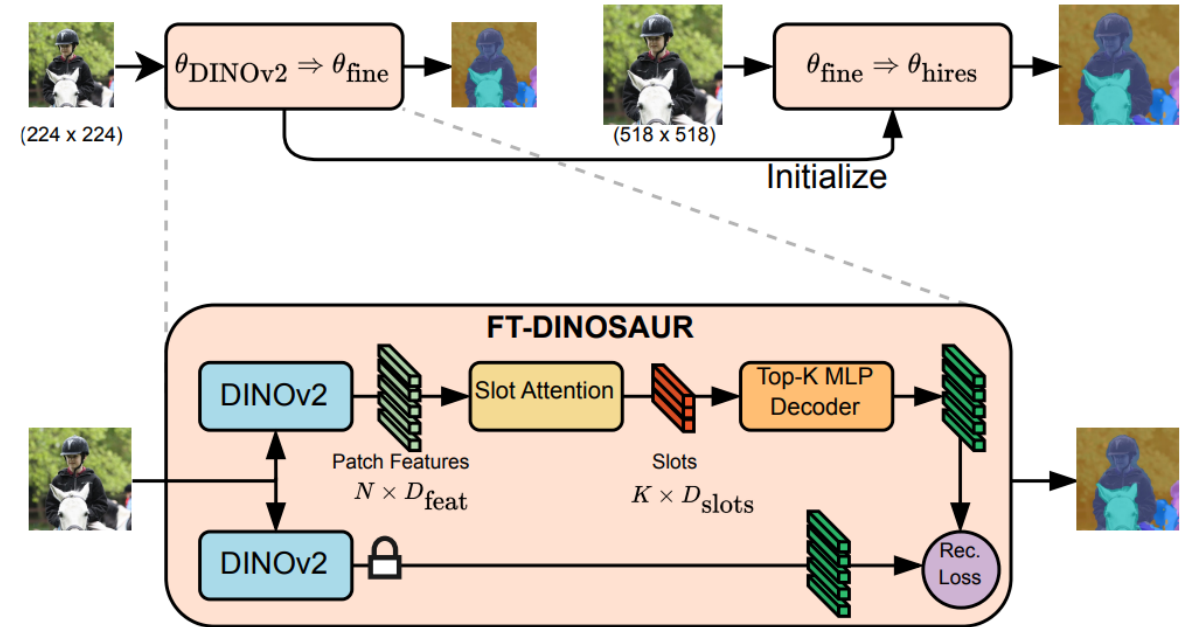


Vanilla slot attention module. Locatello, Francesco, et al., "Object-centric learning with slot attention." NeurIPS 2020.

Motivation & Background



DINOSAUR. Maximilian Seizer, et al., ICLR 2023.



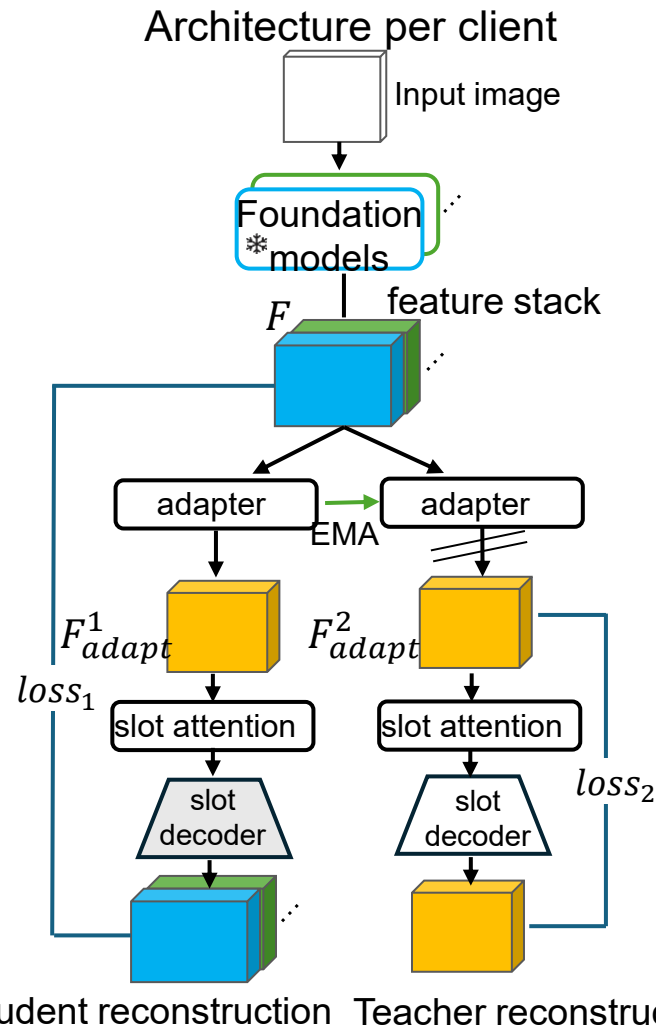
FT-DINOSAUR. Aniket Didolkar, et al, ICLR 2025.

- Slot Attention in real-world images with a foundation model

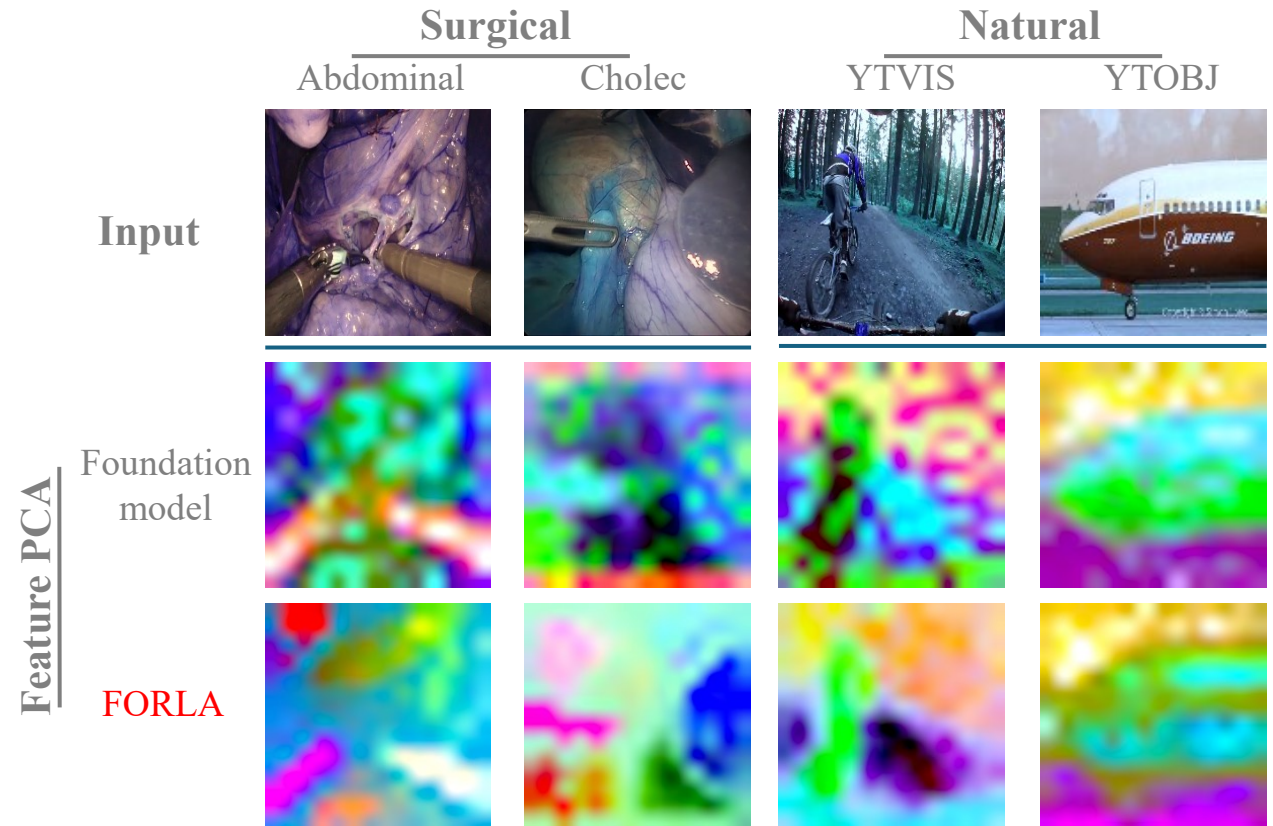
➤ Our key novelty: Bridging Federated Learning and Object-centric Representation Learning

- Slot Attention can be used to fine-tune DINO-based foundation models

Method

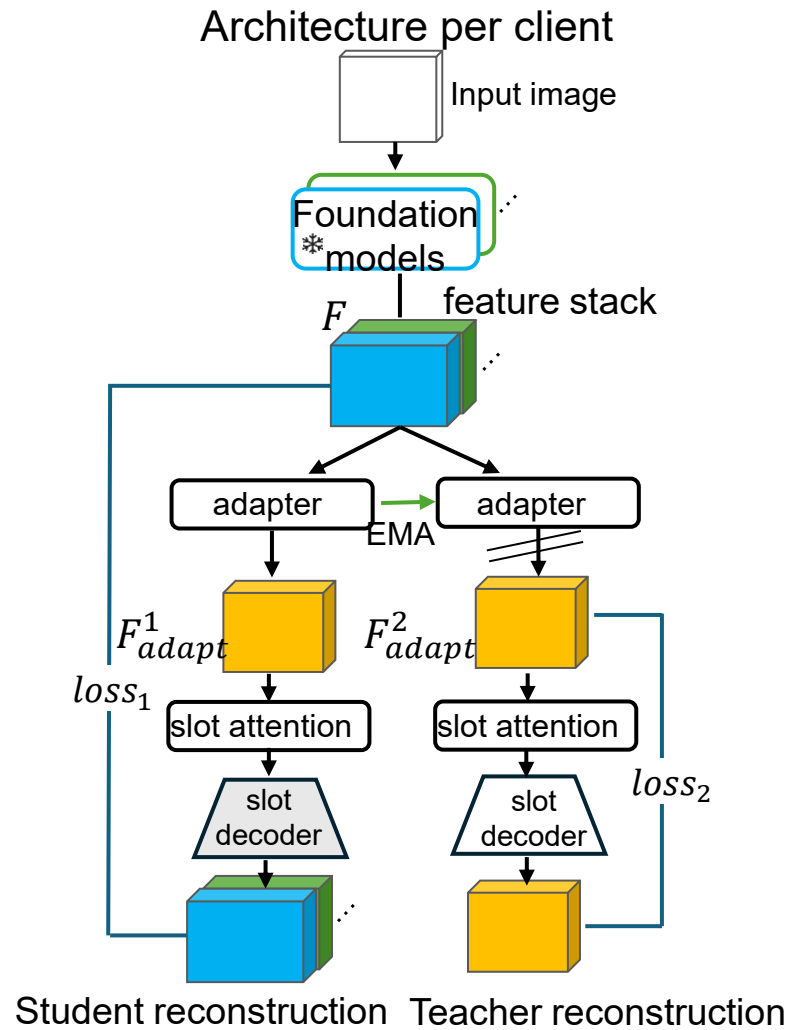


Feature adaptation results

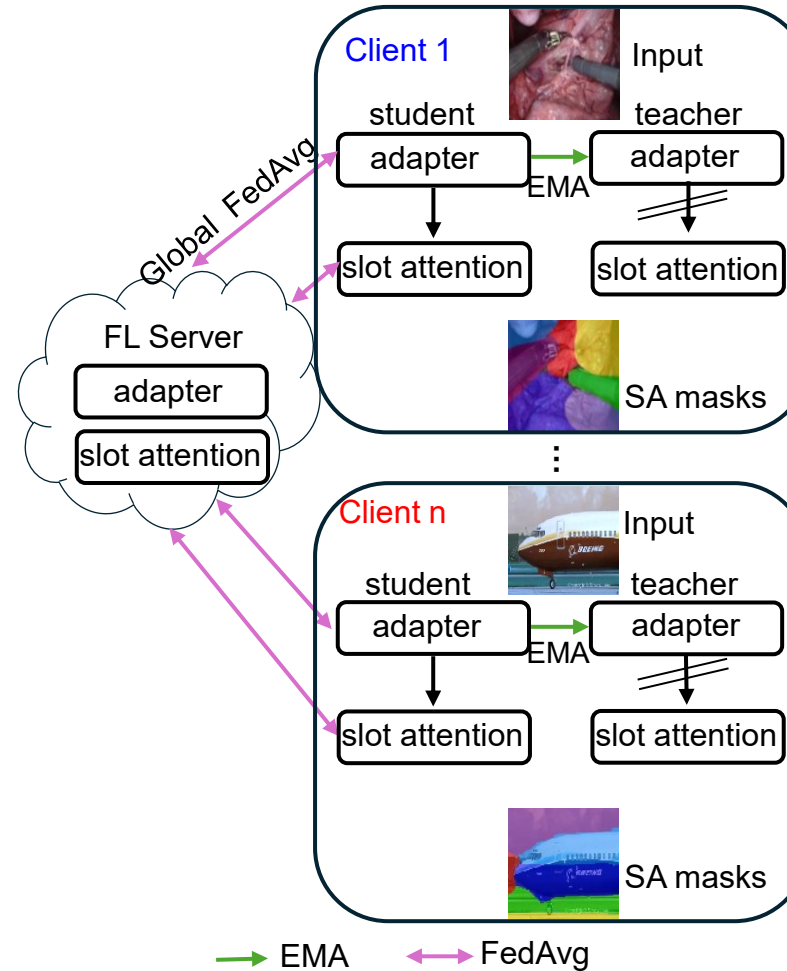


- Observation: Slot attention can adapt the feature to better decompose images into different objects
- Inspired design: Another branch learns to reconstruct the adapted feature

Method

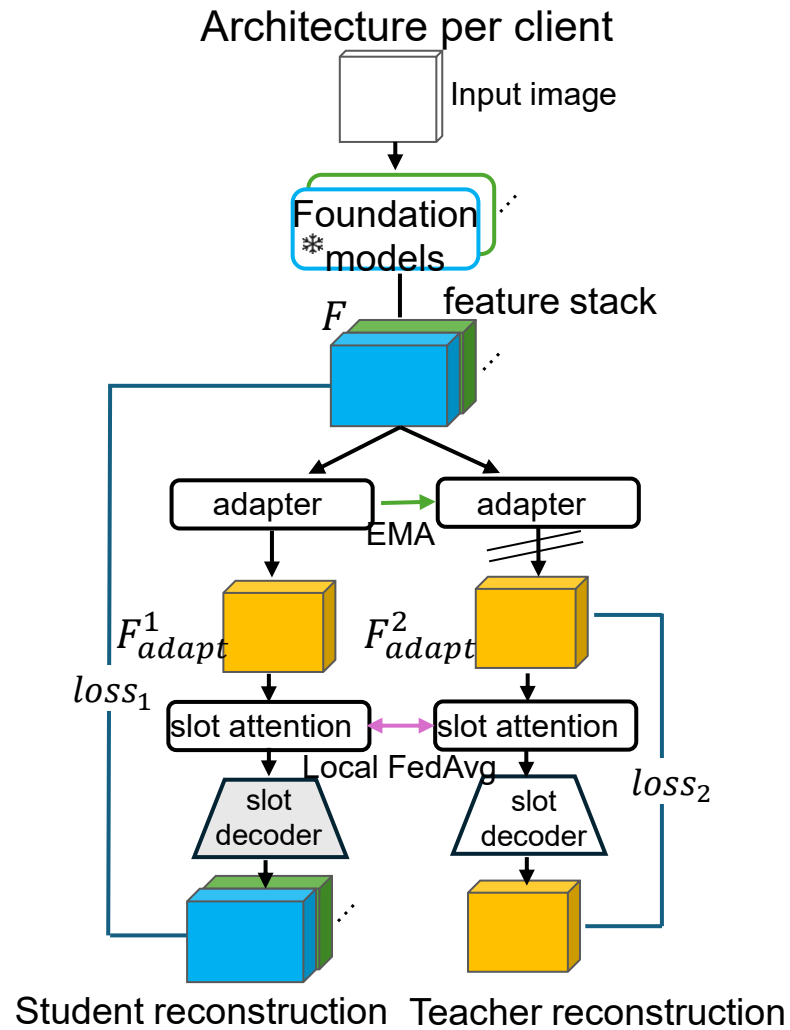


Stage 1: representation distillation & alignment

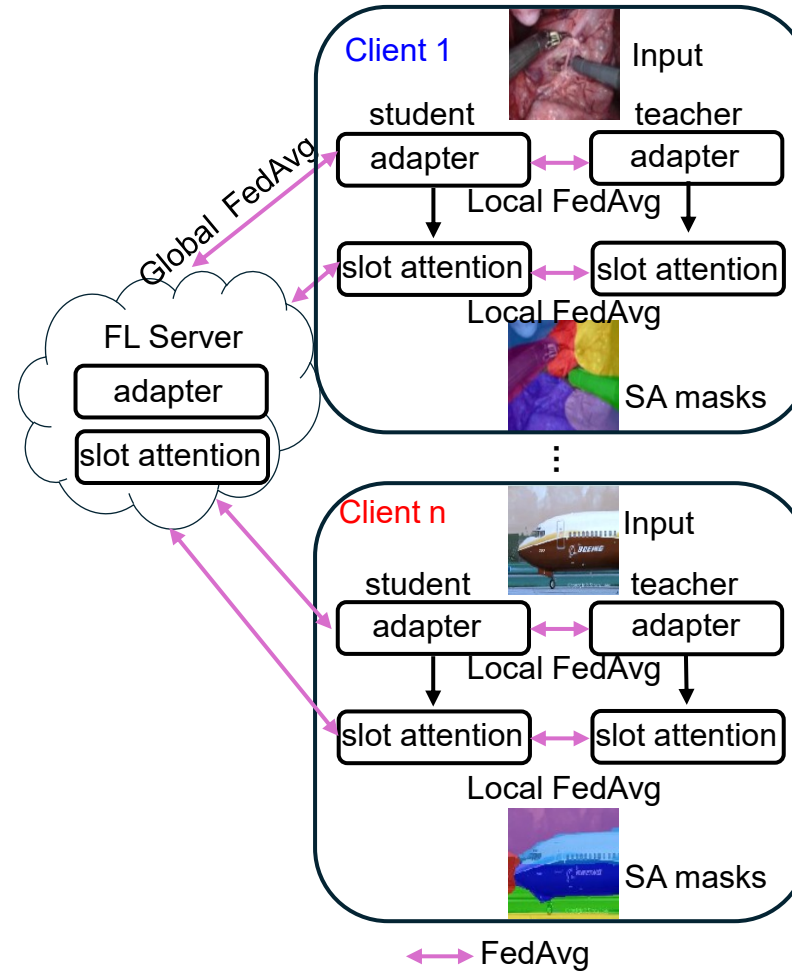


- A two-stage framework for federated object-centric representation learning

Method

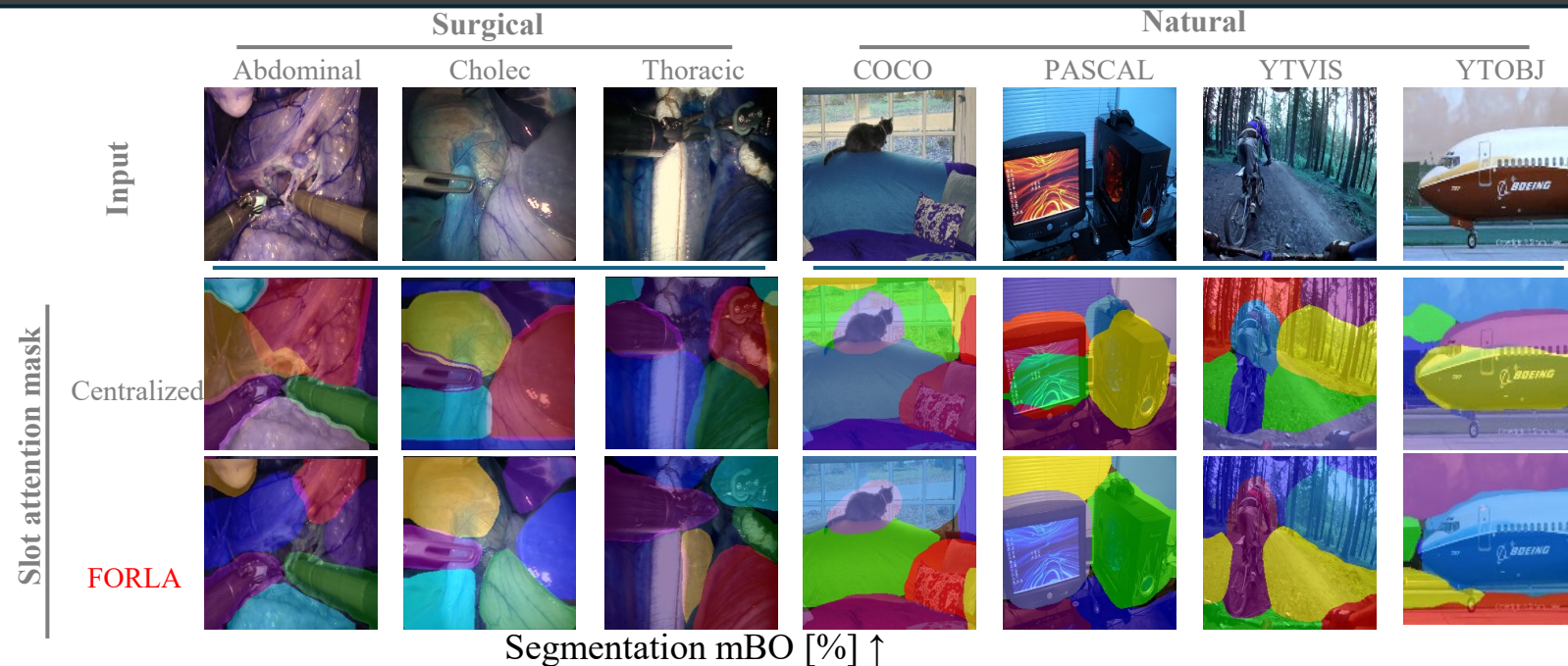


Stage 2: Federated representation re-discovery



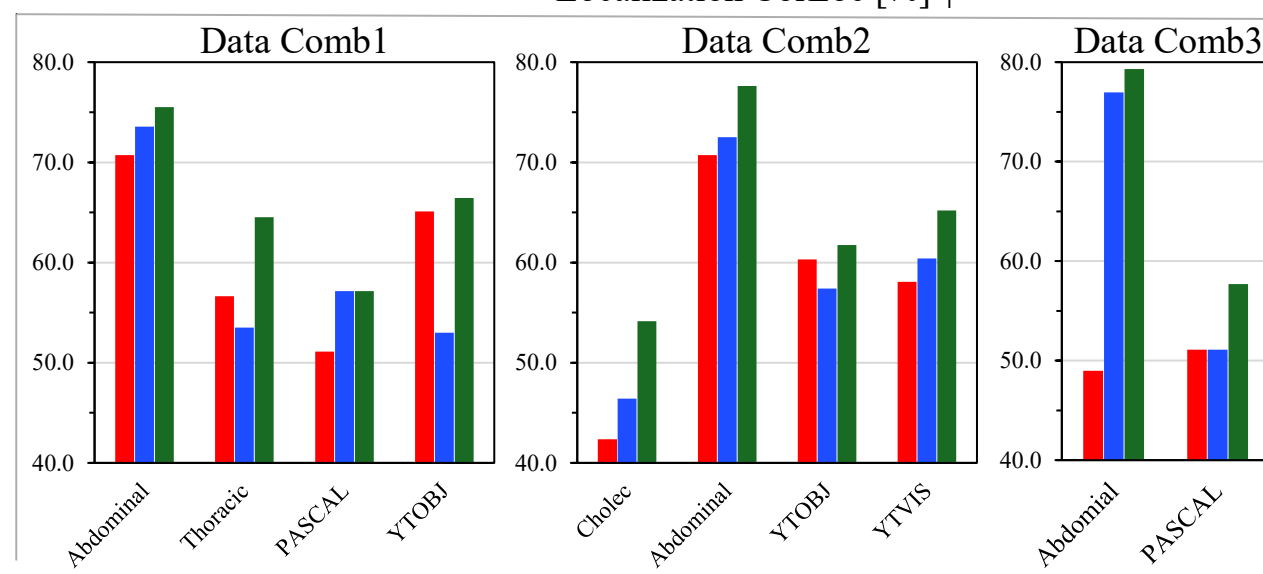
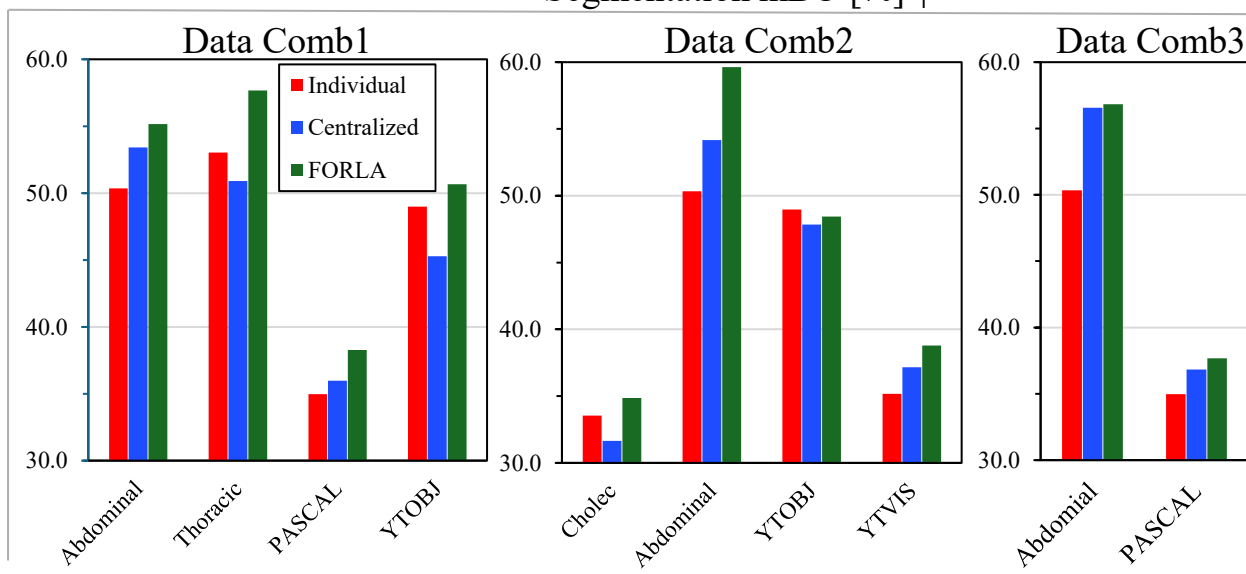
- A two-stage framework for federated object-centric representation learning

Results



-FORLA outperforms centralized training

-Robust to different domain combinations



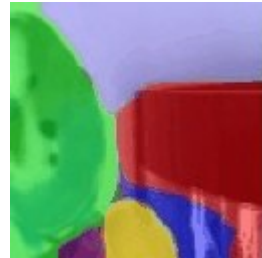
Results



Input



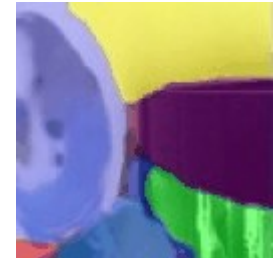
SAM – SA adapted



DINO – SA adapted



FORLA



Conclusion & Future work



- Conclusion

- FORLA is the first to explore federated object-centric learning.
- Mixing all datasets for centralized unsupervised object discovery does not necessarily improve scalability.
- FL can also be a powerful algorithm for knowledge distillation (KD) through teacher–student collaboration.

- Future work

- Incorporate dynamic slot numbers
- Extend FORLA to video-based Slot Attention models

Check our project page: <https://forla-research.github.io/>

