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Continual Segmentation under Joint Nonstationarity

Introducing JASCL: Jointly Anchored and Stabilized Continual Learning

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Problem: Joint Nonstationarity

Real-world segmentation models face simultaneous shifts in classes, domains, and labels.

Class Evolution

New semantic classes appear sequentially (Class-Incremental).

Domain Shift

Input distributions change across sensors/environments (Domain-Incremental).

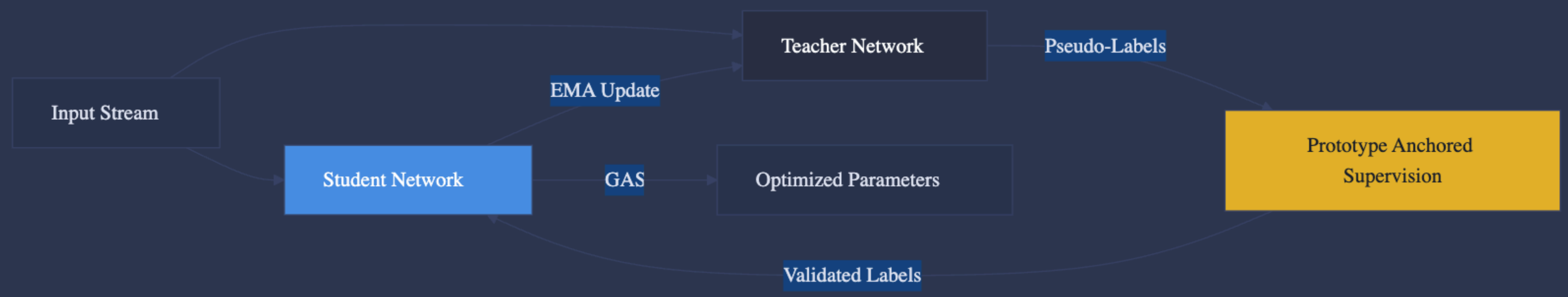
Label Scarcity

Limited supervision available for new sessions (Few-Shot).

Autonomous Driving

Medical Imaging

JASCL Framework Overview



1. Gradient-Adaptive Stabilization (GAS)

Balances stability-plasticity via gradient-scaled perturbations.

2. Prototype Anchored Supervision (PAS)

Anchors semi-supervised learning using class prototypes.

Gradient-Adaptive Stabilization (GAS)

GAS regulates perturbation magnitude using parameter gradients as a proxy for curvature, injecting minimal noise to critical parameters with large gradients and higher noise to overfitting-prone parameters with small gradients.

$$\tilde{W} = W + \tilde{G}^{-1} \odot \mathcal{N}(0, I)$$

This gradient-scaled perturbation approach achieves tighter generalization bounds than isotropic noise methods.

Pseudo-label Validation Criteria

1. Joint Confidence

conf(p, q) > τ_conf

2. Prototype Consistency

sim(p, q) > τ_sim

Theorem: PAS achieves lower asymptotic error than confidence-only methods.

$$\epsilon_\infty(f, \rho) = \frac{(1 - f\gamma)\epsilon_0}{1 - f\gamma(1 - \rho)}$$

By using class prototypes from feature space, PAS prevents error propagation in semi-supervised learning under domain shift, ensuring that pseudo-labels remain anchored to learned semantic concepts.

JASCL Benchmarks

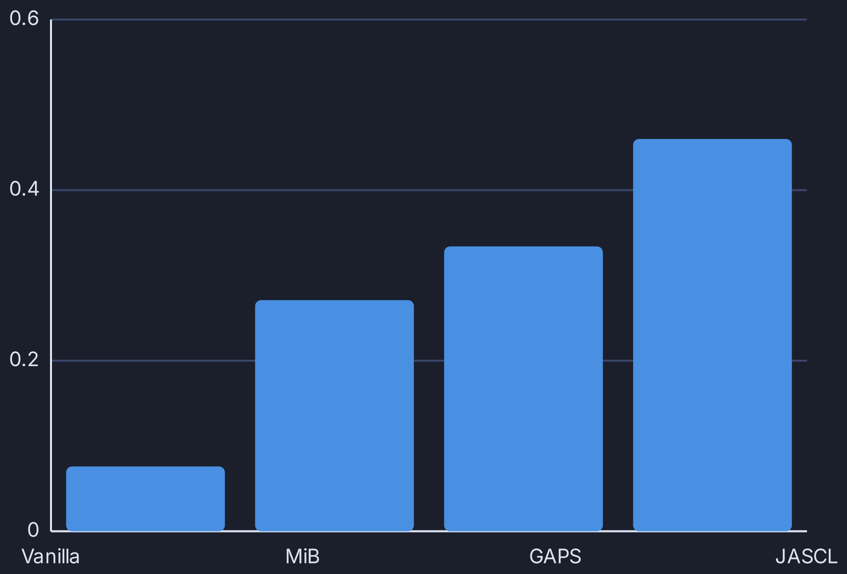
3D Medical Benchmarks

- **Med JASCL-Disjoint:** 6 sessions, 37 classes.
- **Med JASCL-Mixed:** Recurrent classes/domains.
- **Med SS-JASCL:** Semi-supervised (8-30 unlabeled).
- Datasets: TotalSegmentator, AMOS, BraTS, VerSe.

2D Natural Scenes

- **Natural-JASCL:** BDD100K, Cityscapes, IDD.
- **SS-Natural-JASCL:** 400 unlabeled images/class.
- Few-shot setup: 5-10 samples per class.
- Focus: Autonomous driving under domain drift.

Results & Performance



Key Highlights

MedFormer+JASCL: 0.367 → 0.228 (vs. Vanilla collapse)

SAM Improvement: 66.0 → 33.2 → 31.2 mIoU (Natural)

JASCL+GAPS: 27.84 → 25.47 (vs. GAPS 14.45)

Consistent gains across U-Net, SwinUNetr, and SAM backbones

JASCL sustains performance across 6+ sessions with minimal forgetting.

Conclusion

- **JASCL** addresses joint nonstationarity (class, domain, label shifts).
- **GAS** stabilizes optimization via gradient-adaptive noise.
- **PAS** suppresses error propagation in semi-supervised learning.
- Proven reliability across robotics, medical, and autonomous systems.

Open Source Code
https://github.com/prinshul/JASCL.git

Thank You!