Boundary-weighted Logit Consistency Improves Calibration of Segmentation Networks

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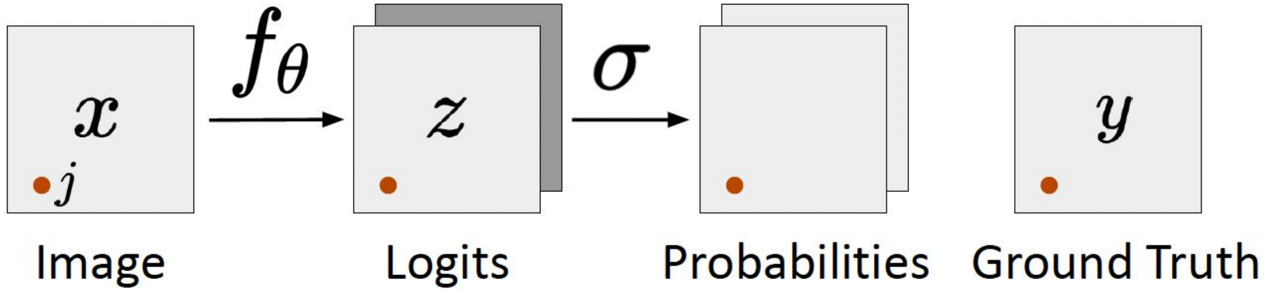
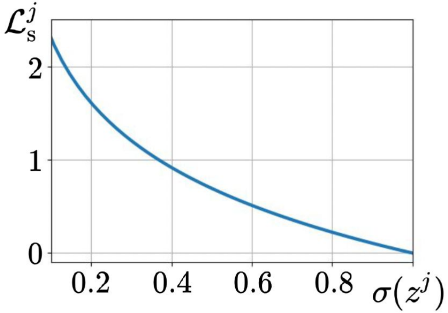
Supervised Deep Segmentation networks



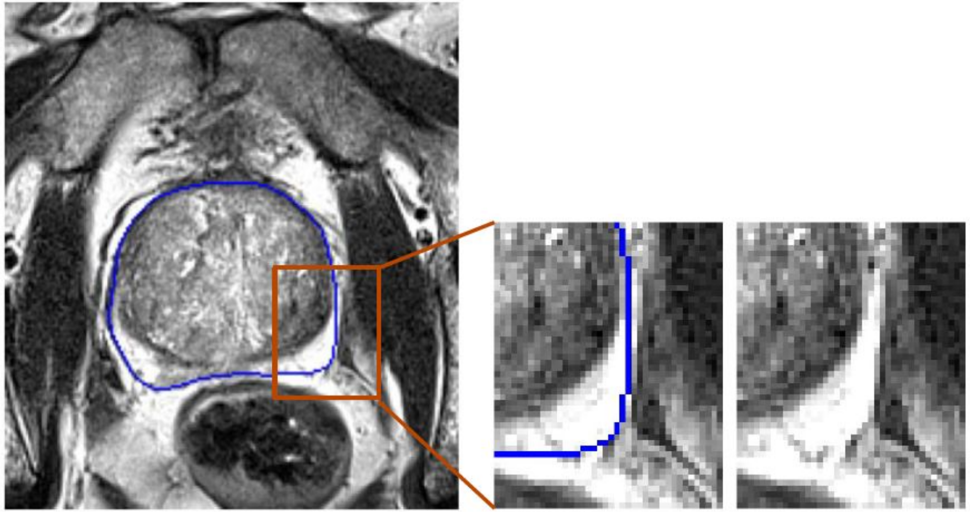
- Cross-entropy loss: $$\mathcal{L}_\mathrm{S}^j = -\sum_{c=1}^{C} y_c^j \log(\sigma(z_c^j))$$



- Encourages high confidence predictions

Ambiguous labels

- Image noise
- Low contrast
- Partial volume effect
- Variability in annotations

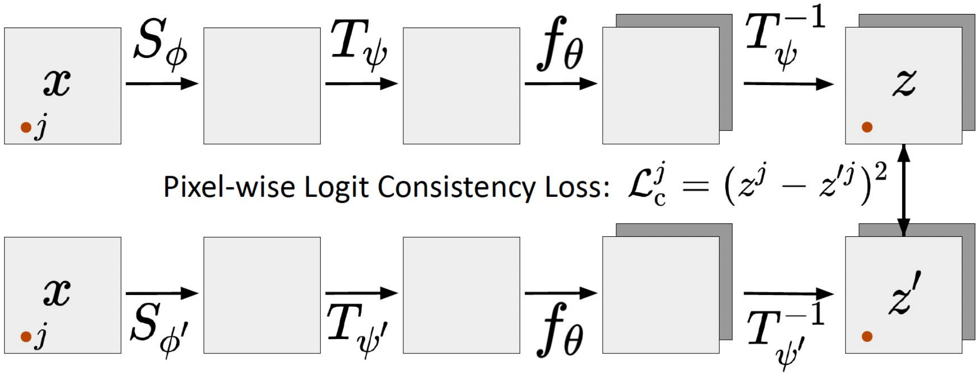


- Over-confidence predictions
- Miscalibrated models

Regularization techniques

- Data augmentation (DA)
  - new input-output pairs
- Consistency Regularization (CR)
  - unsupervised loss
  - unlabeled images

Logit Consistency

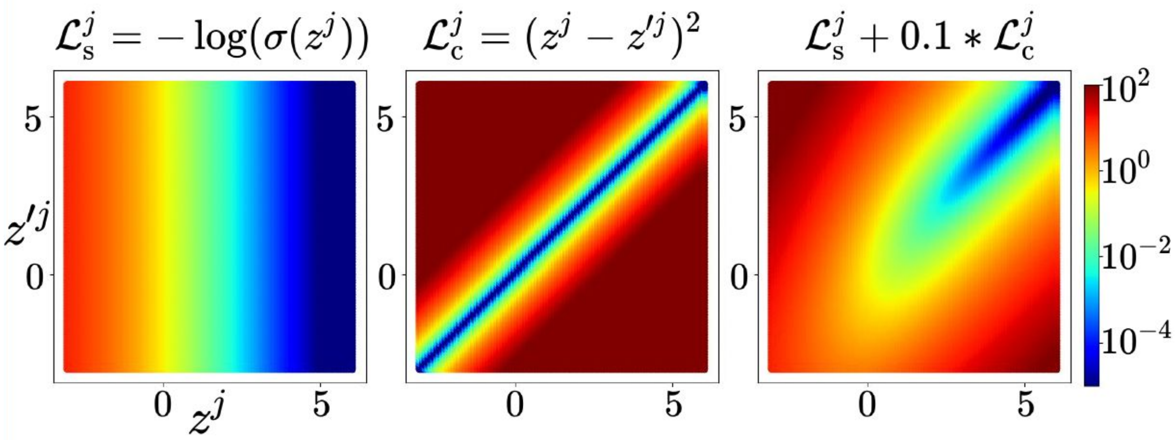


S_ϕ Intensity Transformations (e.g., contrast change, noise addition)

T_ψ Invertible Geometric Transformations (e.g., affine)

$$\mathcal{L}^j = \mathcal{L}_\mathrm{S}^j + \lambda\, \mathcal{L}_\mathrm{C}^j \;= -\sum_{c=1}^{C} y_c^j \log(\sigma(z_c^j)) + \lambda \sum_{c=1}^{C} (z_c^j - z_c'^j)^2$$

Loss landscape for binary segmentation



Prefers large z^j
Independent of z'^j

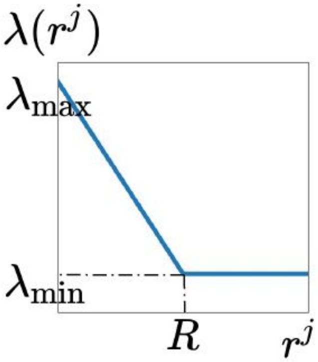
0 along 45 degree line,
increases away from it.

Allows large logits only
near the 45 degree line.

Boundary-weighted consistency regularization (BWCR)

$$\mathcal{L}^j = \mathcal{L}_{\mathrm{s}}^j + \lambda(r^j)\, \mathcal{L}_{\mathrm{c}}^j$$

$$\lambda(r^j) = \lambda_{\max}\left(\frac{max(R - r^j, 0)}{R}\right) + \lambda_{\min}$$



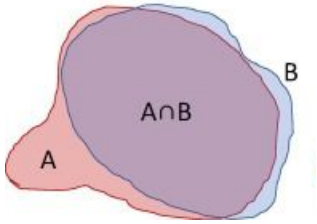
Experimental settings

- Datasets
  - Prostate (NCI, N=70): test 30, val 4 and training {6, 12, 36}
  - Cardiac (ACDC, N=150): test 50, val 5 and training {5, 10, 95}

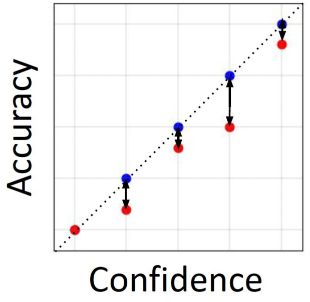
- Baseline
  - Supervised Learning + Data Augmentation (DA)
  - Spatial Varying Label Smoothing (SVLS)
  - Margin Label Smoothing (MLS)

- Evaluation
  - Dice and ECE

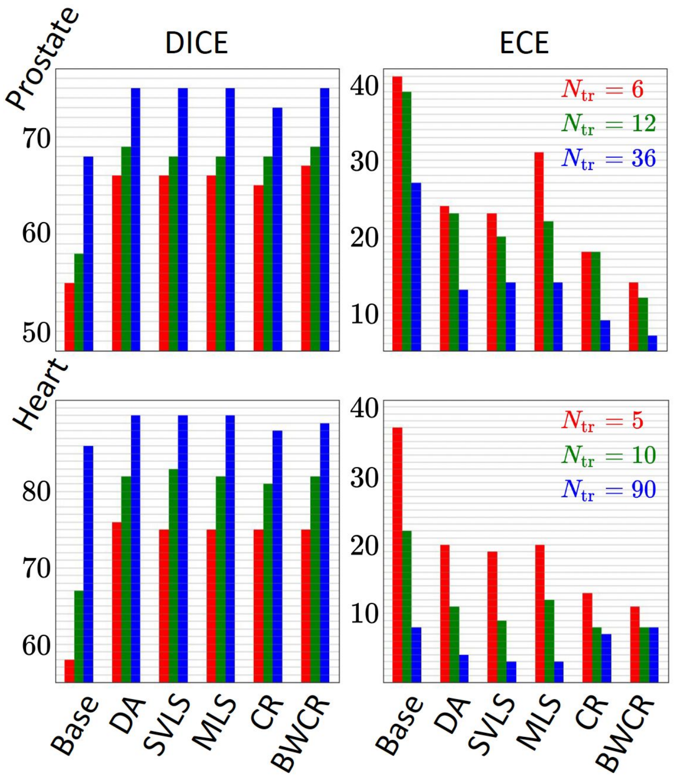
Dice

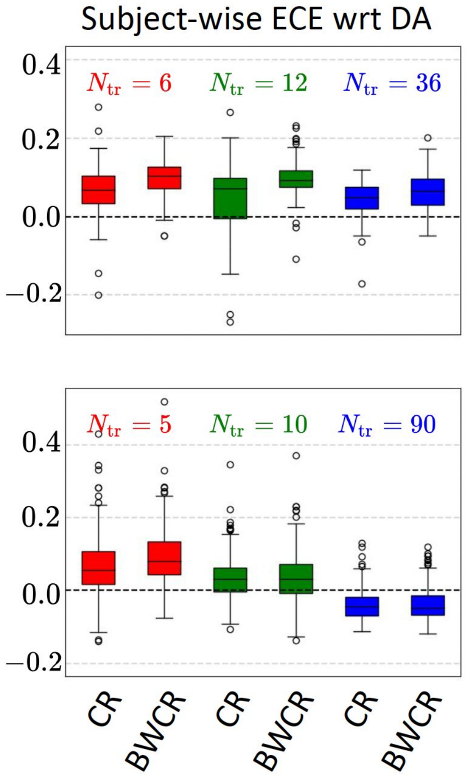


ECE

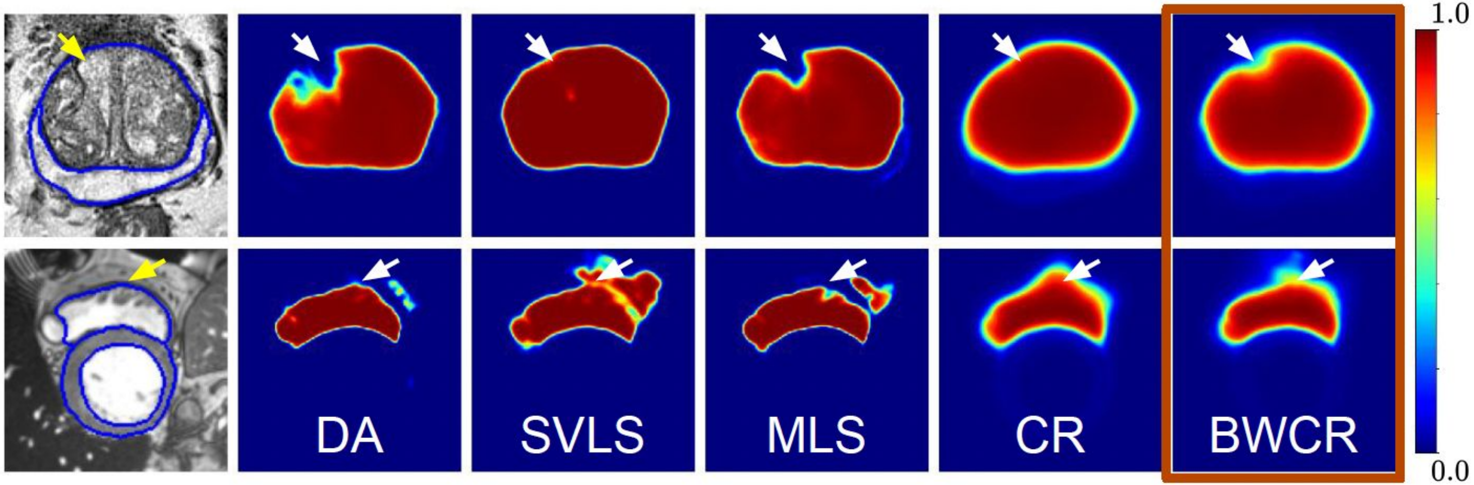


Quantitative Results





Qualitative Results



Conclusion

- Logit consistency prevents confident predictions
    - ambiguous labels
    - improving calibration
- Boundary-weighted emphasizes regularization near tissue boundaries
- Future works
    - other consistency loss functions (cosine similarity or JS divergence)

Interesting Papers at MICCAI 2023

- Asymmetric Contour Uncertainty Estimation for Medical Image Segmentation
- Neural Pre-Processing: A Learning Framework for End-to-end Brain MRI Pre-processing
- Clustering Disease Trajectories in Contrastive Feature Space for Biomarker Proposal in Age-Related Macular Degeneration
- Right for the Wrong Reason: Can Interpretable ML Techniques Detect Spurious Correlations?

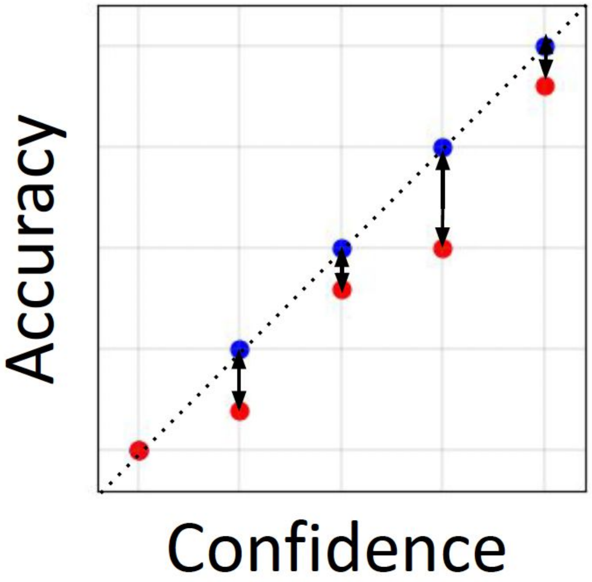
Extra slides

Model Calibration

- Measures prediction probability

- Expected calibration error (ECE)
  - Computed on bins

$$ECE = \sum_{m=1}^{M} \frac{|B_m|}{n} |acc(B_m) - conf(B_m)|$$



Experiments

Supervised Learning + Data Aug. (DA): $\mathcal{L}^j = \mathcal{L}_{\mathrm{s}}^j(y)$

Spatial Varying Label Smoothing (SVLS): $\mathcal{L}^j = \mathcal{L}_{\mathrm{s}}^j(w * y)$

Margin Label Smoothing (MLS): $\mathcal{L}^j = \mathcal{L}_{\mathrm{s}}^j(y) + \lambda\,(z_{\mathrm{max}}^j - m)$

Consistency Regularization (CR) [Ours]: $\mathcal{L}^j = \mathcal{L}_{\mathrm{s}}^j(y) + \lambda\,\mathcal{L}_{\mathrm{c}}^j$

Boundary-Weighted CR (BWCR) [Ours]: $\mathcal{L}^j = \mathcal{L}_{\mathrm{s}}^j(y) + \lambda(r^j)\,\mathcal{L}_{\mathrm{c}}^j$