BACKGROUND & PROBLEM DEFINITION
• Accurate brain structural segmentation is central to nearly all neuroimaging analyses.
• Freesurfer and other traditional tools take 2-4 hrs to segment a volume.
• Freesurfer also has systematic biases.
• Deep Learning based models can increase the efficiency and quality of segmentation.

CONTRIBUTION
• Novel training methodology of scheduling dice and cross entropy loss to optimally train segmentation models.
• Revealed systematic biases in Freesurfer tool and built model free of those biases.
• Inference time < 20 secs / MRI volume

MODEL ARCHITECTURE AND DATA
• Vanilla U-Net architecture

TRAINING METHODOLOGY
• Xavier initialization for model parameters.
• Augmented data using Gaussian blurring, contrast adjustment, rotation and translation.
• Experimented with different loss function schedule:
  o Only dice loss for the entire training period.
  o Only cross entropy loss (CEL) for the entire training period.
  o Both CEL and dice loss for the entire training period.
  o CEL and dice loss for 30 epochs then switched to pure dice loss (Loss scheduling).
• Pre-trained on HCP with Freesurfer labels as the ground truth.
• Fine-tuned on MICCAI train data.

RESULTS
• Evaluated on MICCAI Test Data:

<table>
<thead>
<tr>
<th>Models</th>
<th>Name</th>
<th>Loss Function</th>
<th>Pre-Trained</th>
<th>Fine-Tuned</th>
</tr>
</thead>
<tbody>
<tr>
<td>U-Net</td>
<td>Fixed (w-Dice) Loss</td>
<td>Did not converge</td>
<td></td>
<td></td>
</tr>
<tr>
<td>U-Net</td>
<td>Fixed (w-CEL)</td>
<td>0.7602 ± 0.0185</td>
<td>0.7819 ± 0.072</td>
<td></td>
</tr>
<tr>
<td>U-Net</td>
<td>Fixed (w-CEL + w-dice loss)</td>
<td>0.8649 ± 0.067</td>
<td>0.885 ± 0.042</td>
<td></td>
</tr>
<tr>
<td>U-Net</td>
<td>Loss scheduling</td>
<td>0.798 ± 0.097</td>
<td>0.901 ± 0.045</td>
<td></td>
</tr>
<tr>
<td>QuickNAT</td>
<td>Fixed (w-CEL + dice loss + Boundary Loss)</td>
<td>0.681 ± 0.193</td>
<td>0.857 ± 0.079</td>
<td></td>
</tr>
<tr>
<td>U-Net</td>
<td>Fixed (w-CEL + dice loss + Boundary Loss)</td>
<td>0.681 ± 0.193</td>
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<td></td>
</tr>
</tbody>
</table>

Performance on MICCAI test data. Pre-Trained refers to results when training on auxiliary (Freesurfer) labels, and Fine-Tuned refers to results of fine-tuned model on MICCAI train set
• Vanilla U-Net trained with loss scheduling performed better than the state-of-the-art QuickNAT for the pre-trained model.
• A sample segment is visualized below for all the different pre-trained models.
• Visualization shows the loss scheduling helps the model to get close to Ground Truth (i.e. Freesurfer)
• Coordinated U-net's performance was same as vanilla U-net

SYSTEMATIC BIAS IN FREESURFER
• Difference in performance of pre-trained and fine-tuned model can be seen below:

MODEL FREE OF SYSTEMATIC BIAS
• Visualization of fine-tuned and pre-trained model on the MICCAI test data.

CONCLUSION AND FUTURE WORK
• Loss function and training methodology are as important as the model architecture.
• Deep learning models can overcome biases and inference time is low.
• Future work: Experiment with other data sets and segmentation models to conclusively prove that loss scheduling is a helpful training methodology.
• Future work: Build an open source tool and release models for ~190 segments

References