### Overview

<table>
<thead>
<tr>
<th>Architecture</th>
<th>Data-Aug?</th>
<th>Auxiliary Regularizer</th>
<th>mIoU</th>
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<tbody>
<tr>
<td>VGG-16 hyperscene</td>
<td>yes</td>
<td>Decoder (32 channel)</td>
<td>50.1</td>
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<tr>
<td>VGG-16 hyperscene</td>
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<td>Decoder (128 channel)</td>
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### Semantic Segmentation Results

- **Qualitative:**
  - Corrects large-scale global labeling errors with respect to baseline CNN.
  - Contrast to CRF-like post-processing, which primarily refines boundaries.

- **Quantitative:**
  - Large accuracy boost (≈10% relative) over baseline when training from scratch.
  - Additional improvement step ImageNet pretraining + data augmentation.
  - Gain consistent over many choices of CNN architecture.

### Ablation Experiments

- **Auxiliary Loss Weighting:**
  - Beyond autoencoder architecture, applying our regularizer involves choice of one additional hyperparameter.
  - Can choose relative weight of auxiliary branch loss with respect to primary loss.
  - Robust to this parameter: wide range of weights on the auxiliary loss improves accuracy over the baseline, magnitude of improvement also stable.

- **Encoder Effectiveness:**
  - Regularization effect deteriorates if decoder parameters not held fixed.
  - Performance gains due to label-space model, not dual output pathway architecture.

### Label Model Introspection

**Commonalities with previous [1]:**
- Both provide supplementary training targets.
- Both capture part-like structure.

### References
