A popular approach for semantic segmentation is labeling each super-pixel with one of the required semantic categories. The rich diversity in the appearance of even simple concepts (sky, water, grass) due to the variation in lighting and view-point makes semantic segmentation very challenging. Contextual information from the entire image has been shown to be useful in resolving the ambiguity in super-pixel labeling [1, 2, 4]. The popular approaches for encoding context, MRF or CRF based image models, often make use of simple human-designed interaction potentials that limit the possible complexity of interactions between different parts of the image. This is done to avoid an intractable and computationally intensive inference step.

Recently, an elegant deep recursive neural network approach for semantic segmentation was proposed in [3], referred to as RCPN, Fig. 1. The main idea was to facilitate the propagation of contextual information from each super-pixel to every other super-pixel in a feed-forward manner through random binary parse trees \( T \) on super-pixels. The leaf nodes of \( T \) correspond to super-pixel features and the internal nodes correspond to the features of contiguous merged-regions that result from mergers, as per \( T \), of multiple super-pixel regions. RCPN consists of an assembly of four neural networks - semantic mapper \((F_{\text{sem}})\), combiner \((F_{\text{com}})\), decombiner \((F_{\text{dec}})\) and categorizer \((F_{\text{cat}})\). First, \( F_{\text{sem}} \) mapped visual features of the super-pixels \( v_i \) into semantic space features \( x_i \). This was followed by a recursive combination of semantic features of two adjacent image regions \( x_i \) and \( x_j \), using \( F_{\text{com}} \) to yield the holistic feature vector of the entire image, termed the root feature. Next, the global information contained in the root feature was disseminated to every super-pixel in the image, using \( F_{\text{dec}} \), followed by classification of the enhanced super-pixel features \( x_i \) by \( F_{\text{cat}} \). RCPN has the potential to learn complex non-linear interaction between different parts of the image that resulted in impressive real-time performances on standard semantic segmentation datasets.

This paper shows that the presence of bypass-error paths in RCPN can lead to sub-optimal parameter learning and proposes a simple modification to improve the learning. Specifically, we propose to include the classification loss of pure-nodes to the RCPN loss function that originally consisted of classification loss of the super-pixels only. Pure-nodes are the internal nodes of \( T \) that correspond to merged-regions consisting of pixels of a single semantic category only. Therefore, pure-nodes can be used as classification targets for learning RCPN parameters. The resulting model is termed Pure-node RCPN or PN-RCPN. It leads to these three immediate benefits - a) increased labels per image; around 65% of all internal-nodes are pure-nodes for three different datasets b) deeper and stronger gradients and c) explicitly forcing the combiner to learn meaningful combinations of two image-regions.

We use an example to understand the benefits of PN-RCPN over RCPN, depicted with the help of Fig. 2(a) and Fig. 2(b), respectively. The figures show the left-half of a random parse tree for an image \( I \) with 5 super-pixels. We denote, \( e_{\text{cat}}^{\text{i}} \in \mathbb{R}^n \) as the error at enhanced super-pixel nodes;