# Boosting Semi-Supervised Semantic Segmentation with Probabilistic Representations

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## Introduction

TASK:

- Pixel-wise contrastive learning in Computer vision.
- Semi-supervised semantic segmentation.

MOTIVATION:

- Improve the quality of pixel-wise representation considering the probability, allow them to perform better under the inaccutate pseudo labels

CONTRIBUTION:

- Define pixel-wise representations from a new perspective of probability theory.
- Through modelling the mapping from pixels to representations as the probability via multivariate Gaussian distributions, tune the contribution of the ambiguous representations to tolerate the risk of inaccurate pseudo-labels.
- Define prototypes in the form of distributions, which indicates the confidence of a class, while the point prototype cannot.
- Propose a Probabilistic Representation Contrastive Learning (PRCL) framework that improves representation quality by taking its probability into consideration.

## Methodology

PROBABILISTIC REPRESENTATION


- We denote the probability of mapping a pixel $\boldsymbol{x}_i$ to a representation $\boldsymbol{z}_i$ as $p(\boldsymbol{z}_i|\boldsymbol{x}_i)$ and define the representation as a random variable following it. For simplicity, we take the form of multivariate Gaussian distribution $\mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\sigma}^2\boldsymbol{I})$ as:

$$p(\boldsymbol{z}_i|\boldsymbol{x}_i) = \mathcal{N}(\boldsymbol{z}; \boldsymbol{\mu}_i, \boldsymbol{\sigma}_i^2\boldsymbol{I}). \tag{1}$$

DISTRIBUTION PROTOTYPE

- The prototype is the posterior distribution after the $n^{th}$ observations $\{\boldsymbol{z}_1, \boldsymbol{z}_2, ..., \boldsymbol{z}_n\}$. Under the assumption that all the observations are conditionally independent, the distribution prototype can be derived as:

$$p(\boldsymbol{\rho}|\boldsymbol{z}_1, \boldsymbol{z}_2, ..., \boldsymbol{z}_{n+1}) = \alpha \frac{p(\boldsymbol{\rho}|\boldsymbol{z}_{n+1})}{p(\boldsymbol{\rho})} p(\boldsymbol{\rho}|\boldsymbol{z}_1, \boldsymbol{z}_2, ..., \boldsymbol{z}_n), \tag{2}$$

where $\alpha$ is a normalization factor. In addition to Equation 1, we can rewrite the prototype as

$$\boldsymbol{\rho} \sim \mathcal{N}(\hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\sigma}}^2\boldsymbol{I}), \tag{3}$$

where

$$\hat{\boldsymbol{\mu}} = \sum_{i=1}^{n} \frac{\hat{\boldsymbol{\sigma}}^2}{\boldsymbol{\sigma}_i^2}\boldsymbol{\mu}_i \tag{4}$$

$$\frac{1}{\hat{\boldsymbol{\sigma}}^2} = \sum_{i=1}^{n} \frac{1}{\boldsymbol{\sigma}_i^2}. \tag{5}$$

SIMILARITY

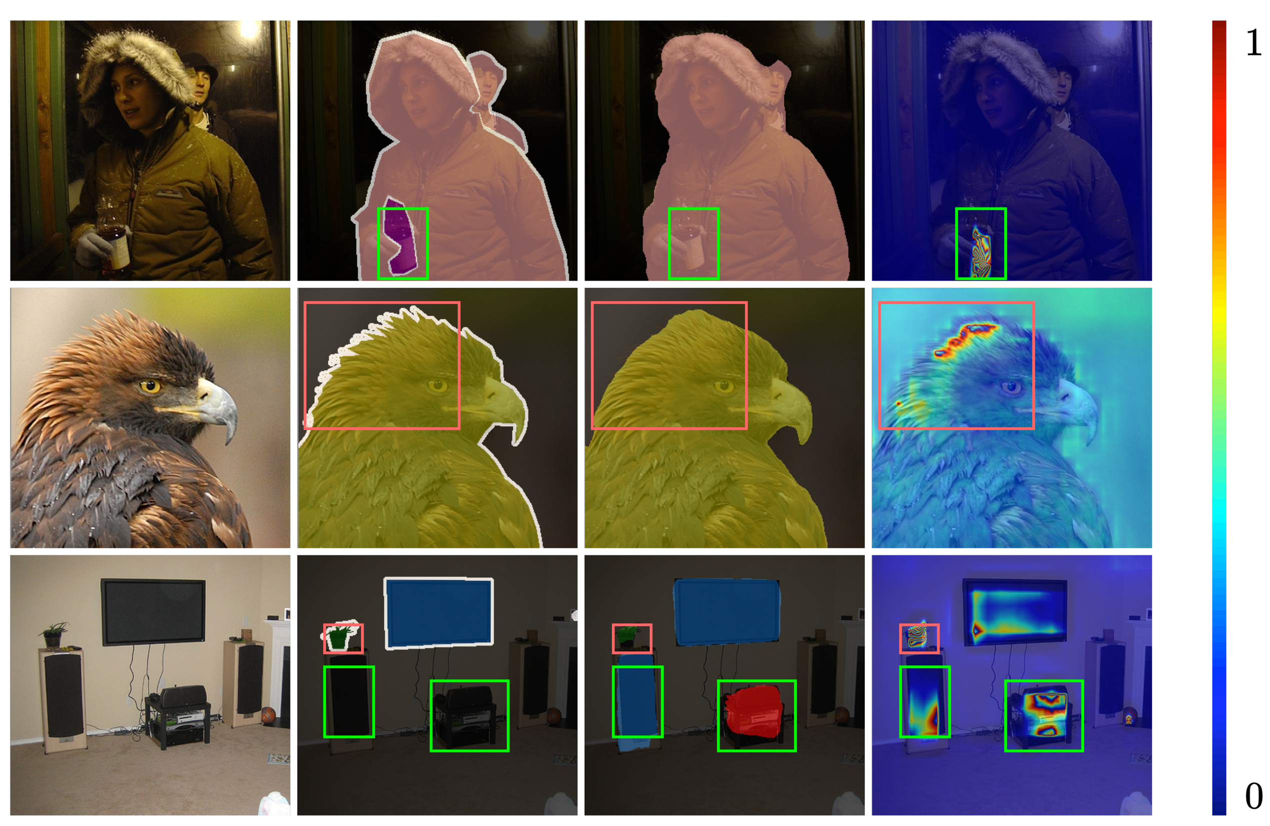
- We leverage Mutual Likelihood Score (MLS) to measure the similarity between two distributions $\boldsymbol{z}_i$ and $\boldsymbol{z}_j$, as follows:

$$\begin{aligned} MLS(\boldsymbol{z}_i, \boldsymbol{z}_j) =& log(p(\boldsymbol{z_i} = \boldsymbol{z}_j)) \\ =& -\frac{1}{2}\sum_{l=1}^{D}\left(\frac{(\mu_i^{(l)} - \mu_j^{(l)})^2}{\sigma_i^{2(l)} + \sigma_j^{2(l)}} + log(\sigma_i^{2(l)} + \sigma_j^{2(l)})\right) \\ & -\frac{D}{2}log2\pi, \end{aligned} \tag{6}$$

- In the first term, the weight of $\ell_2$ distance is small when the $\boldsymbol{\sigma}^2$ is large, which indicates that the similarity between $\boldsymbol{z}_i$ and $\boldsymbol{z}_j$ becomes lower due to the low probabilities, even if they are very similar in the view of $\ell_2$ distance. The probability has been taken into consideration besides the simple similarity measure for representations learning.
- In the second term, $\boldsymbol{\sigma}^2$ is penalized for the low probability representations, which makes all the representations more reliable.
- Besides, $\boldsymbol{\sigma}^2$ and $\boldsymbol{\mu}$ can interact with each other. The learnable $\boldsymbol{\sigma}^2$ is associated with $\ell_2$ distance. This means that $\boldsymbol{\sigma}^2$ can be learned via the relations among representations. On the other hand, the $\boldsymbol{\mu}$ can also be optimized via the $\boldsymbol{\sigma}^2$. This is consistent with intuitive cognition.

## Results

In Figure , columns from left to right represent input image, ground-truth, pseudo-label, and probability, respectively. For the fourth column, the red color represents the large $\boldsymbol{\sigma}^2$ (low probability). The green boxes mark the mismatches caused by inaccurate pseudo-labels (e.g., person and bottle) and the red boxes mark the fuzzy pixels (e.g., furry edge of the bird). These two cases are highlighted by $\boldsymbol{\sigma}^2$ and make low contribution in training process.




(a) Image (b) Ground-Truth (c) Pseudo-label (d) Probability