DICE LOSS

In deep learning and computer vision, people are working hard on feature extraction to output meaningful representations for various f vision tasks. In some tasks, we only focus on geometry of the objects, regardless of colors, textures and illuminations etc. That' Image segmentation comes in.

As part of the Assignment, we have original image in jpg format, using json file input(drawing set of polygons) we created mask imag for our problem) which is in .png format. our task is predict the boundary detection like road,animal,person ... etc, total we have labels. But Extracting clean and meaningful object boundaries is not easy.

Can we use Cross entropy as loss function?
When using cross entropy loss, the statistical distributions of labels play a big role in training accuracy. The more unbalanced the istributions are, the more difficult the training will be, the improvement is not significant nor the intrinsic issue of cross entro is solved. In cross entropy loss, the loss is calculated as the average of per-pixel loss, and the per-pixel loss is calculated dis without knowing whether its adjacent pixels are boundaries or not. As a result, cross entropy loss only considers loss in a micro se er than considering it globally, which is not enough for image level prediction.

Which is better than Cross entropy for image segementation
Dice Loss

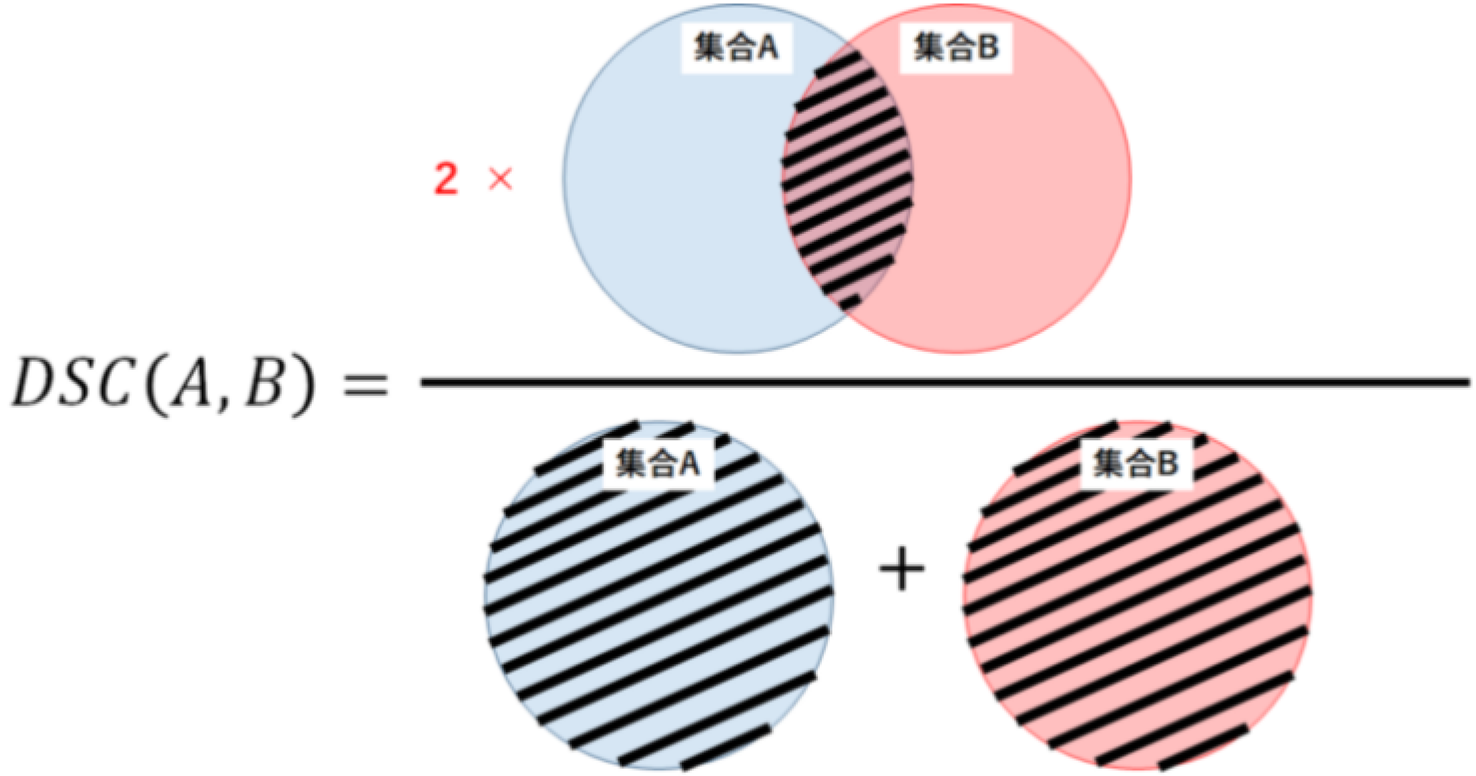
Range of Dice loss

This measure ranges from 0 to 1 where a Dice coefficient of 1 denotes perfect and complete overlap. The Dice coefficient was origina loped for binary data, and can be calculated as:

$$Dice = \frac{2\,|A \cap B|}{|A| + |B|}$$

where |A∩B| represents the common elements between sets A and B, and |A| represents the number of elements in set A (and likewise fc B).

For the case of evaluating a Dice coefficient on predicted segmentation masks, we can approximate |A∩B| as the element-wise multipli etween the prediction and target mask, and then sum the resulting matrix.



Idea behind the Dice loss or how it's works

From the perspective of set theory, in which the Dice coefficient (DSC) is a measure of overlap between two sets. For example, if tw and B overlap perfectly, DSC gets its maximum value to 1. Otherwise, DSC starts to decrease, getting to its minimum value to 0 if th ts don ‘t overlap at all. Therefore, the range of DSC is between 0 and 1, the larger the better.

In Image detection tasks, the Mask image and predicted boundary pixels can be viewed as two sets. By leveraging Dice loss, the two s trained to overlap little by little.

In [ ]: