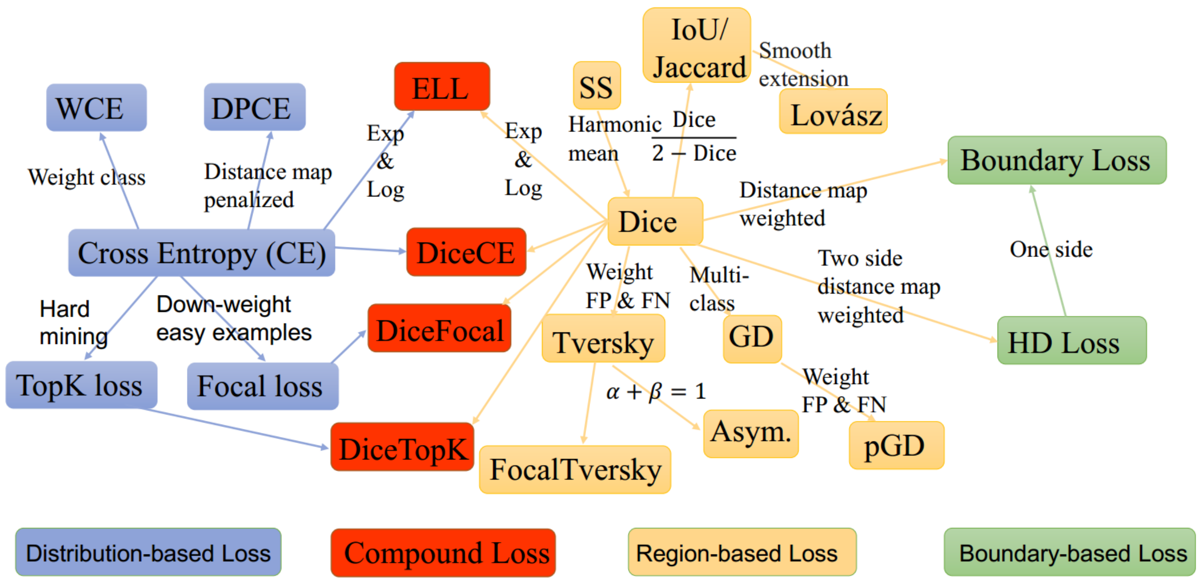
Potential Loss Function Components

Task: To come up with a loss function that focus on constraining the shape of GT and predicted shape.

From literature review we can see that compound loss functions are the most robust losses, especially for the highly imbalanced segmentation tasks. So combination of the following loss functions have to be evaluated. (https://www.sciencedirect.com/science/article/abs/pii/S1361841521000815)



1. Dice Loss
    a. Compares the predicted segmentation mask with the ground truth mask to maximize overlap.
    b. Use the predicted segmentation output after the mask decoder and compute the Dice Loss with the ground truth mask.
2. Boundary Loss
    a. Allows for accurate predictions near object boundaries.

   b. Targets the boundaries of the predicted segmentation mask from the mask decoder. Compute the spatial gradient (Sobel operator) of both predicted and ground truth segmentation masks to calculate the difference.

3. Attention Map Regularization
   a. Ensures the self-attention and cross-attention mechanisms focus on meaningful cardiac regions.
   b. Applies to self-attention and cross-attention layers in the shape prior module and image encoder.
4. KL Divergence Loss (Shape Priors)
   a. Ensures the predicted shape distribution matches that of the learned cardiac shape priors.
   b. Compute KL Divergence between the latent representation of shape priors and the predicted shape tokens.
5. Hausdorff Distance Loss
   a. Minimizes the maximum boundary distance between predicted and ground truth volumes, which is critical in 3D segmentation.
   b. Compute the Hausdorff distance between the surfaces of predicted and ground truth segmentations.
6. Shape Alignment Loss*
   a. Enforces alignment between the shape prior tokens and the predicted segmentation map.
   b. Compare the shape representation derived from cross-attention with the ground truth or shape prior representations.