Question 1: What is the issue with IoU loss that GIoU loss solves involving bounding boxes in object detection?

Question 2: What are the two ideas behind the two categories of loss functions used in facial recognition? Specifically, they each measure something but this thing is different in either type.

Question 3: What does ramp loss improve upon in regards to hinge loss? What makes it more robust?

Answer 1: IoU loss, as given by the formula below, only works in the case that the predicted box overlaps the ground truth box. GIoU solves this by slowly increasing the predicted boxes size to get closer and closer to the ground truth box in the case that the two do not overlap.

IoU loss	
Formula	$L = -\ln(IoU) = -\ln \frac{I}{U}$, where, I is the intersection area of two boxes, U is the union area of two boxes.
Algorithm	UnitBox [55]. The specific calculation formulas of I and U can be found in [55]
Explanation	For each pixel (i, j), the predicted box is $B^p = (x_t^p, x_b^p, x_l^p, x_r^p)$, the ground truth box is $B^g = (x_t^g, x_b^g, x_l^g, x_r^g)$, where, (t, b, l, r) represent the distance between this pixel and the top, bottom, left, right bounds of ground truth, respectively

Answer 2: The first quantifies the difference between samples by measuring Euclidian space distance and the second measures the angular space distance.

Answer 3: The Hinge loss value of the outlier is very large and outliers play a leading role in determining the decision boundary, so the model will reduce the accuracy of normal samples to reduce such loss, and finally reduce the overall classification accuracy. Ramp loss improves upon this by giving an upper bound to the maxim loss which dampens the effect of outliers. In SVMs it also has the effect of reducing the number of support vectors used to find the decision boundary.