

January
2020

The Real World Weight Cross Entropy Loss Function

So they say that cross entropy which is the standard loss function does not do well when a class is underrepresented. So they present a new loss function the Real World Cost function.

So normal categorical cross entropy:
for one example.

eq. 0

$$- \sum_{\text{num classes}} y^k \cdot \log(h_{\theta}(x))$$

prob of true

prob of loss from model

Now people also said (not these guys)
lets give more weight to the loss of the underrepresented classes

eq1 -

$$\sum_{k=1}^K w_k \cdot y^k \cdot \log(h_{\theta}(x))$$

weight for class k

So then these guy come around
and propose a separate weight for
missing positive VS missing negative
so... that's pretty much what they do.

eq. 2

$$-\sum_{\text{num classes}}^K W_{mcfp}^k \cdot Y^k \cdot \log(h_{\theta}(X, k)) + \sum^{K'} W_{mcfn}^{k'} \cdot Y^{k'} \cdot \log(1 - h_{\theta}(X, k'))$$

\swarrow marginal cost of making a false positive $K' \neq K$ \searrow marginal cost of making a false negative

So to test this they take MNIST
~7,000 of each class for say class
"0" zero they label the first 630 them as zero
+ the rest are left out. do this
for the next 630 + so on that
way 10 dataset + then 100 if done
for each number. so for one
dataset 630 (positive) / 63,000 (negative)
so 1% positives so very skewed data

They set the MCFN High 2000
(cost of not identifying rare disease) +
the MCFP not so High. ^{cost} (set of a retest)
100

In the results they found that they
had fewer false negatives but more
false positives.

Then they find that in the real world
this would result in lower cost. This
makes sense if you set the marginal
costs correctly then we would optimize
for that.

★ Note in the binary case this is
equivalent to doing eq.1 where the
weight is a ratio of $MFNC/MFPC$

★ Note the marginal cost are not learned
params and set by experts of the domain

find similar result in the multiclass case