Learning with Symmetric Label Noise: The Importance of Being Unhinged

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Q: Can we design a loss that is convex but robust to label noise?  
A: Yes! Just unhinge the hinge loss from SVMs.

Q: Is there an accurate classification rule that is robust to label noise?  
A: Yes! Just use the mean classifier.

The Symmetric Label Noise Problem

Want: Samples from notionally “clean” distribution \( D \)  
Get: Samples from “corrupted” distribution \( \bar{D} \), where labels are flipped with probability \( \sigma \)

The Usual Approach – Convex Surrogates

The usual approach to learning classifiers is via the minimization of convex potential loss function over a class of linear functions (hinge loss for the SVM, logistic loss for logistic regression, exponential for boosting and so on...). This approach works well if the training samples are clean, but if they are corrupted by noise.

(Long & Servedio, 2010): with a linear function class, any convex potential minimiser resorts to random guessing under nonzero symmetric label noise. This leads to the folk theorem that for robustness to label noise, one needs a non-convex loss.

Corruption-Corrected Losses

(Natarajan et al., 2013): introduced a method to correct for symmetric label noise. For any loss \( \ell \), they associated a corrected loss,
\[
\bar{\ell}(y, v) = \frac{(1 - \sigma)\ell(y, v) - \sigma\ell(-y, v)}{1 - 2\sigma}
\]
with the property that for all classifiers \( f \), \( R_{\bar{\ell}}(f, D) = R_\ell(f, \bar{D}) \). These losses give “bonus points” for correctly classifying a noisy label. Noise corrected losses allow one to learn from corrupted data. If you know \( \sigma \)......

One Line Summary

"While the truth is rarely pure, it can be simple"