CS231n- Lecture 3

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1 Optimization

1.1 Multiclass SVM loss

Given an example (x_i, y_i) where x_i is the image and where y_i is the (integer) label, and using the shorthand for the scores vector: $s = f(x_i, W)$ The SVM Loss has the form

$$L_i = \sum_{j \neq y_i} max(0, s_j - s_{y_i} + 1)$$

cat 3.2 1.3 2.2 car 5.1 4.9 2.5 frog -1.7 2.0 -3.1 Losses: 2.9 0 10.9

Q: What if the sum was instead over all class? (i.e including $j=y_i$) A: Score is just being inflated by one as $j=y_i$

Q: What if mean was used instead of sum?

A: Pointless as it is only a difference of $c_i * L_i$

Q: What if instead you use $L_i = \sum_{j \neq y_i} max(0, s_j - s_{y_i} + 1)^2$ A: This changes the loss function.

Q: Min/Max values? A: Min=0. Max= Infinite

Q: Usually at initialization W are small numbers so all s = 0. What is the loss?

A: Loss becomes $number\ of\ classes-1$. This serves as a good sanity check.

Example numpy code for:

$$L_i = \sum_{j \neq y_i} max(0, s_j - s_{y_i} + 1)$$

$$\begin{array}{lll} def & L_{\text{-i-vectorized}}\left(x, \ y, \ W\right); \\ & scores = W. \ dot\left(x\right) \\ & margins = np. \\ maximum(0, \ scores - scores\left[y\right] + 1) \\ & margins\left[y\right] = 0 \\ & loss_{\text{-i}} = np. \\ sum(margins) \\ & return & loss_{\text{-i}} \end{array}$$

We now have

$$f(x, W) = Wx$$

$$L = \frac{1}{N} \sum_{j \neq y_i} max(0, s_j - s_{y_i} + 1)$$

Suppose we found a W such that L=0. Is this W unique?

No. If we double W. Loss is the same. Same goes if you multiply it with a number n: n >= 1

So there is a huge subspace of W for which this is optimal.

Weight Regularisation

Weight Regularisation
$$L = \frac{1}{N} \sum_{i=1}^{N} \sum_{j \neq y_i} \max(0, f(x_i; W)_j - f(x_i, W)_{y_i} + 1) + \lambda R(W)$$
 In Common use:

L2 Regularization: $R(W) = \sum_{k} \sum_{l} W_{k,l}^2$ L1 Regularization: $R(W) = \sum_{k} \sum_{l} |W_{k,l}|$ Elastic Net(L1+ L2): $R(W) = \sum_{k} \sum_{l} \beta W_{k,l}^2 + |W_{k,l}|$

Max norm regularization(will see later)

Dropout(Will see later)

L2 is most popular. λ indicate the regularisation strength.