

Activity 19: Hinge Loss and Support Vector Machines

Example: Handwritten digit recognition

$$x = \text{vec}\left(\begin{array}{|c|} \hline 9 \\ \hline \end{array}\right) \quad \hat{y} \approx x^T w$$



Wikipedia MNIST dataset performance, April 2020

Type	Classifier	Error rate (%)
Linear classifier	Pairwise linear classifier	7.6 ^[8]
Support-vector machine (SVM)	Virtual SVM , deg-9 poly, 2-pixel jittered	0.56 ^[25]
Convolutional neural network	Committee of 20 CNNs with Squeeze-and-Excitation ^[29]	0.17 ^[30]

Hinge Loss and Support Vector Machines

Classifying new data:

$$\hat{y} = \text{sign}(\mathbf{x}^T \mathbf{w})$$

features (points to \mathbf{x})
weights (points to \mathbf{w})

Training a classifier:

$$\min_{\mathbf{w}} \ell(\mathbf{w}) + \lambda r(\mathbf{w})$$

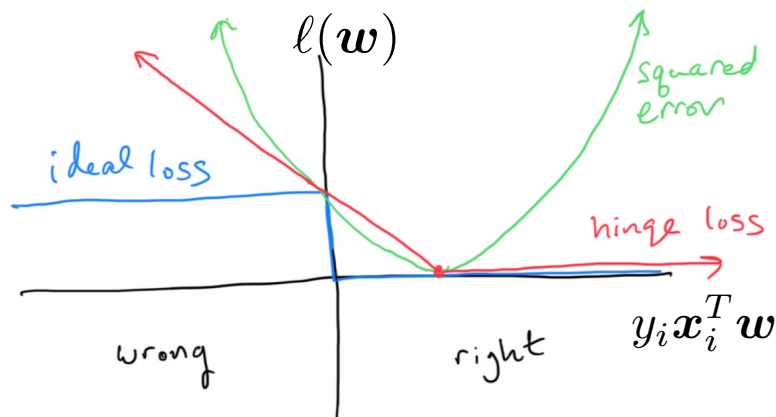
Loss function (points to $\ell(\mathbf{w})$)

$\ell(\mathbf{w})$:

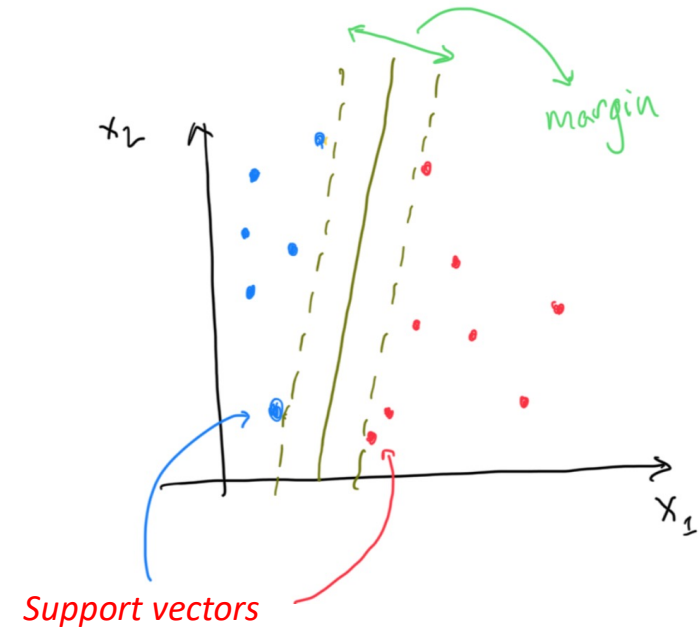
- squared error $\|\mathbf{X}\mathbf{w} - \mathbf{y}\|_2^2$
- ideal (0-1) loss $\sum_i \frac{1}{2} |y_i - \text{sign}(\mathbf{x}_i^T \mathbf{w})|$
- hinge loss $\sum_i (1 - y_i \mathbf{x}_i^T \mathbf{w})_+$
- logistic loss $\log(1 + e^{-y_i \mathbf{x}_i^T \mathbf{w}})$

positive when correct classification,
negative when wrong

$$y_i \mathbf{x}_i^T \mathbf{w}$$



Support Vector Machines



maximize margin
s.t. correct classification

↓
minimize $\|\tilde{\mathbf{w}}\|^2$
s.t. $y_i \mathbf{x}_i^T \mathbf{w} \geq 1$ for $i = 1, \dots$

↓
$$\min_{\mathbf{w}} \sum_i (1 - y_i \mathbf{x}_i^T \mathbf{w})_+ + \lambda \|\tilde{\mathbf{w}}\|_2^2$$