Kernelized SVM 25 October 2021 19:38 I had a doubt earlier: Once you solve the Dual Problem, you will get your support vectors (those having non-zero a:). After getting Doubt... your support vectors, you can derive your w*. $\omega = \sum_{i=1}^{\infty} \alpha_i y_i x_i$ This raised a question in my mind, if we used a kernel function to get the d's, then we won't be able to use this formula because we won't have the Xi's in the higher dimensions. On going through 'Hands On Machine Learning with Scikit - Learn, Keras and Tensor Flow', I came to know that the calculating of ω and b for Kernalized SVM is very similar to that of 'Simple' SVM. Given the &'s from solving the Dual Problem: $\omega = \sum_{i=1}^{m} x_i y_i \varphi(x^{(i)})$ where $\phi(x^{(i)})$ is the transformed training example $x^{(i)}$. However, we do not physically have $\phi(x^{(i)})$ because all a Kernel gives us is transformed inner-products $\phi(x^{(i)})$, $\phi(x^{(j)})$ to plug into the Dual Problem. We actually don't need w and b to get our hypothesis function, w.x +b working! $h_{\omega,b}(\phi(x^{(j)})) = \omega.\phi(x^{(j)}) + b$ $h_{\omega,b}(\phi(x^{(i)})) = \begin{bmatrix} & \propto; y; \phi(x^{(i)}) \end{bmatrix} \cdot \phi(x^{(i)}) + b$

$h_{\omega,b}(\phi(x^{(j)})) = \left[\sum_{i=1}^{m} \alpha_i y_i \phi(x^{(i)})\right] \cdot \phi(x^{(i)})$	< _(i,)) + P
$h_{\omega,b}(\phi(x^{(j)})) = \left[\sum_{i=1}^{m} \alpha_i y_i (\phi(x^{(i)}), \phi(x^{(j)})\right]$))] + b
$h_{\omega,b}(\phi(x^{(j)})) = \sum_{i=1}^{m} \alpha_i y_i K(x^{(i)}, x^{(j)})$	$+$ b $\frac{1}{2}$ where $\alpha_i > 0$
Note that since of; ≠ 0 only -	for SVs, thus we
will need the transformed inr	
only with the SVs.	
m, m	
$b = \frac{1}{m} \sum_{i=1}^{m} (y_i - \omega_i \phi(x^{(i)})) = \frac{1}{m} \sum_{i=1}^{m}$	$\left(\begin{array}{ccc} y_i - \left(\sum_{j=1}^{\infty} \alpha_i y_i \phi(x^{(j)})\right), \phi(x^{(j)}) \end{array}\right)$
$b = \frac{1}{m} \sum_{i=1}^{m} \left[y_i - \sum_{j=1}^{m} \alpha_j y_j \phi(x^{(j)}) \cdot \phi(x^{(i)}) \right]$	
$b = \frac{1}{m} \left[y_i - \sum_{j=1}^{m} \alpha_j y_j K(x^{(i)}, x^{(j)}) \right]$	
m i=1 -	
Finally our hyperplane becomes:	
	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$
$h_{\omega,b}(\phi(x^{(j)})) = \sum_{i=1}^{m} \alpha_i y_i K(x^{(i)}, x^{(j)})$	$+\frac{1}{m}\sum_{i=1}^{n}\left[y_{i}-\sum_{j=1}^{n}\alpha_{j}y_{j}K(x^{n},x^{n})\right]$