

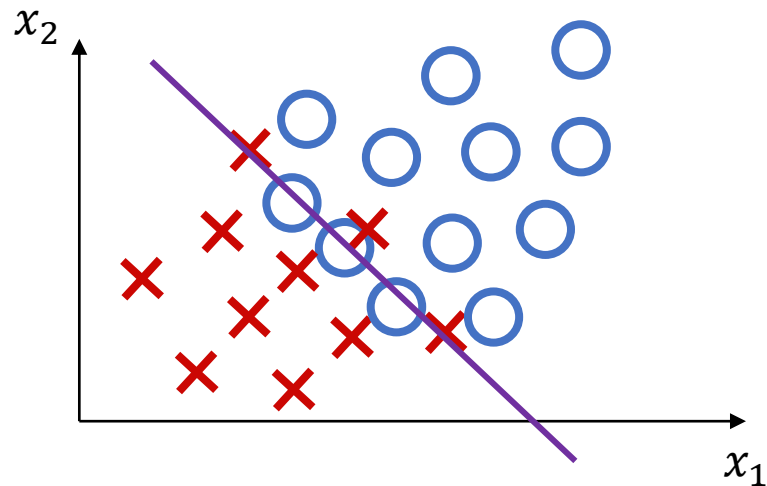
CSE 575

Statistical Machine Learning

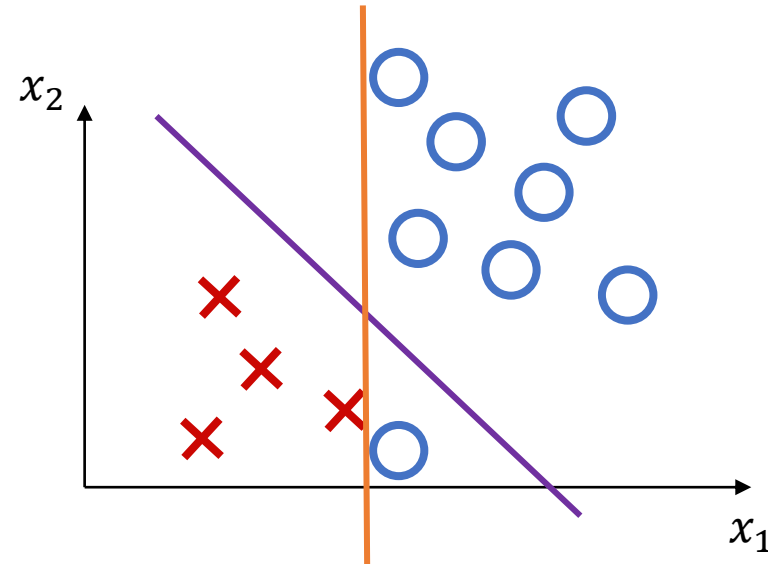
Lecture 11
YooJung Choi
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Recap: Soft-margin SVM

For better generalization, we may want to allow the classifier to *make small mistakes* in exchange for *large margins*

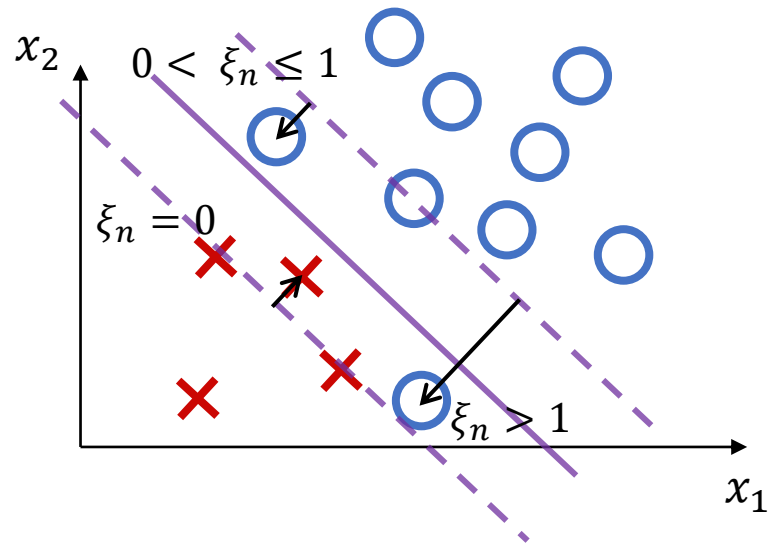


Overlapping distributions



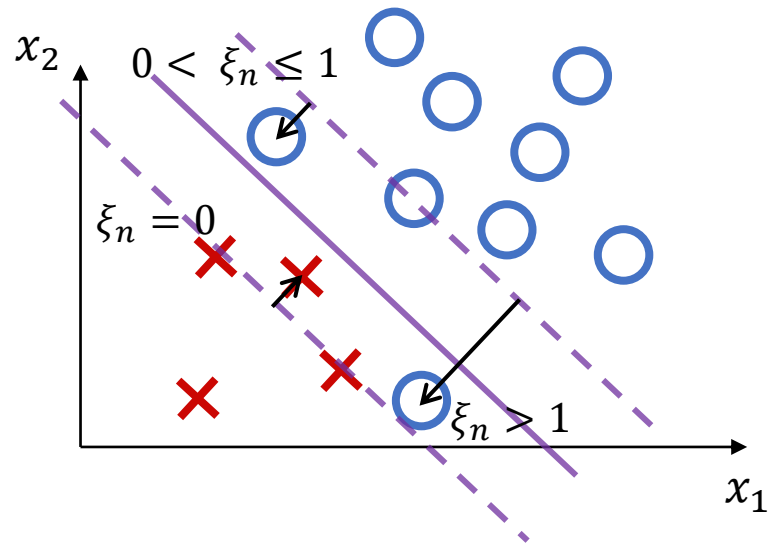
Outliers

Recap: Soft-margin SVM



- Introducing slack variables $\xi_n \geq 0$:
 - $\xi_n = 0$: \mathbf{x}_n is correctly classified on the right side of margin boundary
 - $0 < \xi_n \leq 1$: \mathbf{x}_n is correctly classified but on the wrong side of margin boundary (*margin violation*)
 - $\xi_n > 1$: \mathbf{x}_n is misclassified
- Intuition: we want the total slack to be small

Soft-margin SVM



- For a positive example \mathbf{x}_n :

$$\xi_n \geq 1 - (\mathbf{w}^T \mathbf{x}_n + b)$$

- For a negative example \mathbf{x}_n :

$$\xi_n \geq (\mathbf{w}^T \mathbf{x}_n + b) - (-1)$$

- Combining using t_n :

$$t_n(\mathbf{w}^T \mathbf{x}_n + b) \geq 1 - \xi_n, \quad \forall n$$

Soft-margin SVM

Dual formulation

$$\operatorname{argmin}_{\mathbf{w}, b} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{n=1}^N \xi_n$$

$$\text{s. t. } t_n(\mathbf{w}^T \mathbf{x}_n + b) \geq 1 - \xi_n \quad \forall n$$

$$\xi_n \geq 0 \quad \forall n$$

$$\operatorname{argmax}_{\mathbf{a}} \sum_{n=1}^N a_n - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N a_i a_j t_i t_j k(\mathbf{x}_i, \mathbf{x}_j)$$

$$\text{s. t. } 0 \leq a_n \leq C \quad \forall n$$

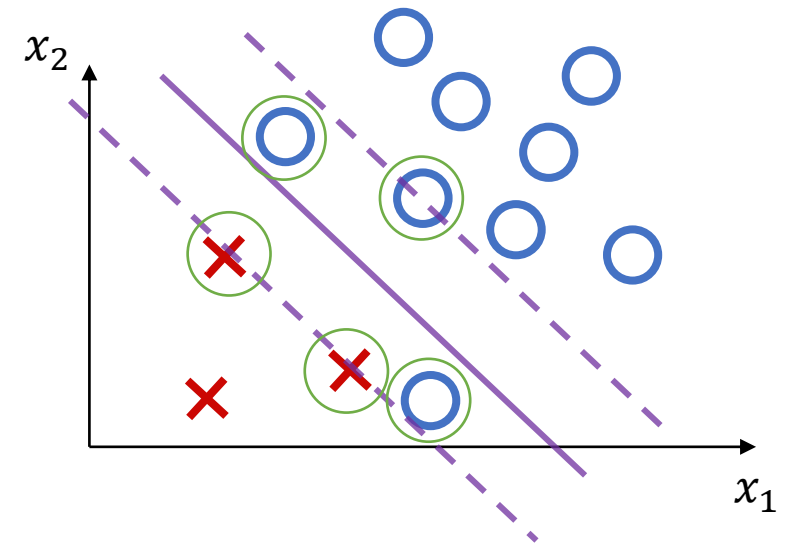
$$\sum_{n=1}^N a_n t_n = 0$$

- Again, *support vectors* are \mathbf{x}_n such that $a_n > 0$.

They are the examples that satisfy:

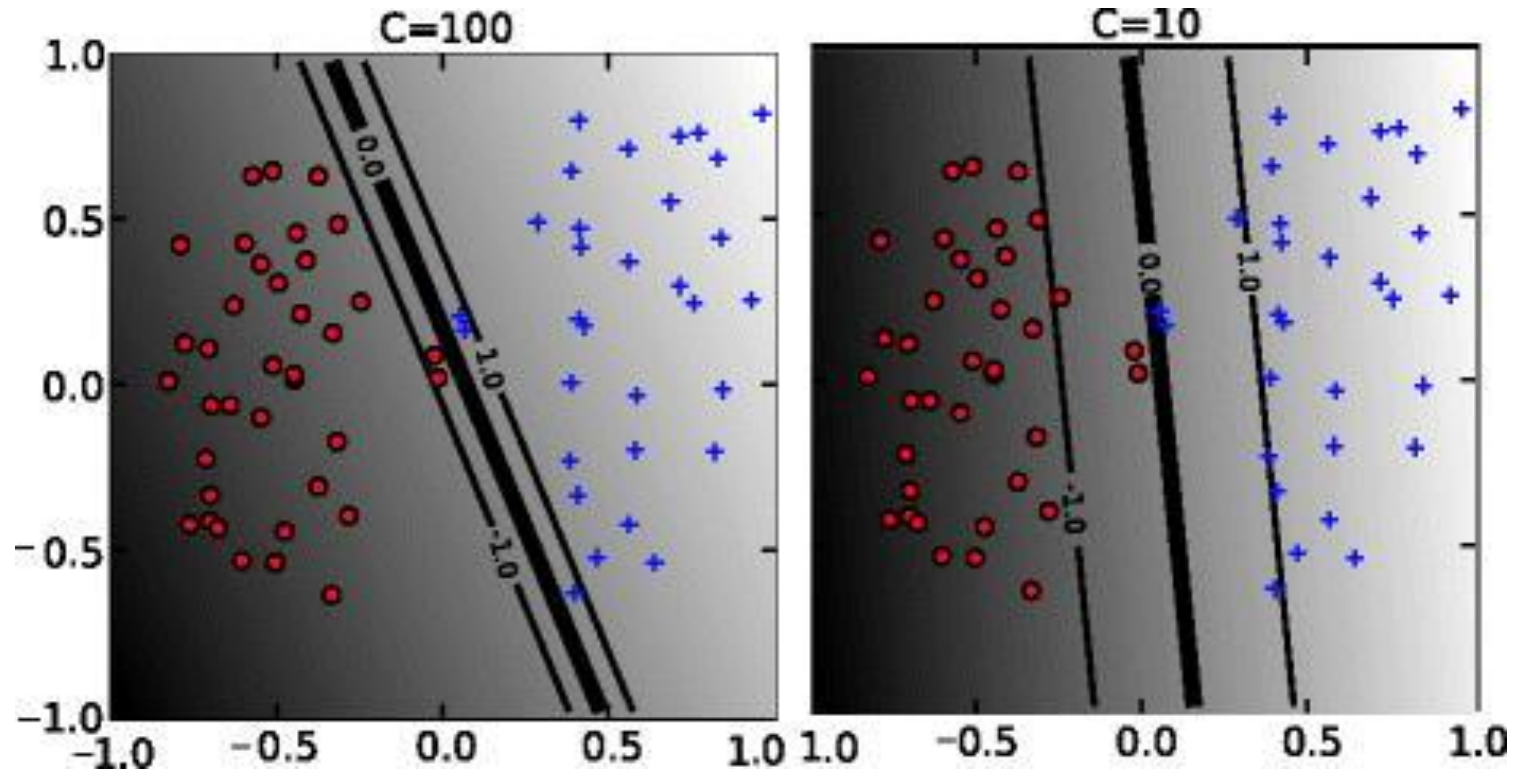
$$t_n(\mathbf{w}^T \mathbf{x}_n + b) = 1 - \xi_n$$

i.e. do not satisfy $t_n(\mathbf{w}^T \mathbf{x}_n + b) > 1$



Soft-margin SVM

$$\begin{aligned} \operatorname{argmin}_{\mathbf{w}, b} \quad & \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{n=1}^N \xi_n \\ \text{s.t.} \quad & t_n(\mathbf{w}^T \mathbf{x}_n + b) \geq 1 - \xi_n \quad \forall n \\ & \xi_n \geq 0 \quad \forall n \end{aligned}$$



Hinge loss

$$\operatorname{argmin}_{\mathbf{w}, b} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{n=1}^N \xi_n$$

$$\text{s. t. } t_n(\mathbf{w}^T \mathbf{x}_n + b) \geq 1 - \xi_n \quad \forall n$$

$$\xi_n \geq 0 \quad \forall n$$

$$\operatorname{argmin}_{\mathbf{w}, b} \frac{1}{n} \sum_{n=1}^N \xi_n + \lambda \|\mathbf{w}\|^2$$

$$\text{s. t. } \xi_n \geq 1 - t_n(\mathbf{w}^T \mathbf{x}_n + b) \quad \forall n$$

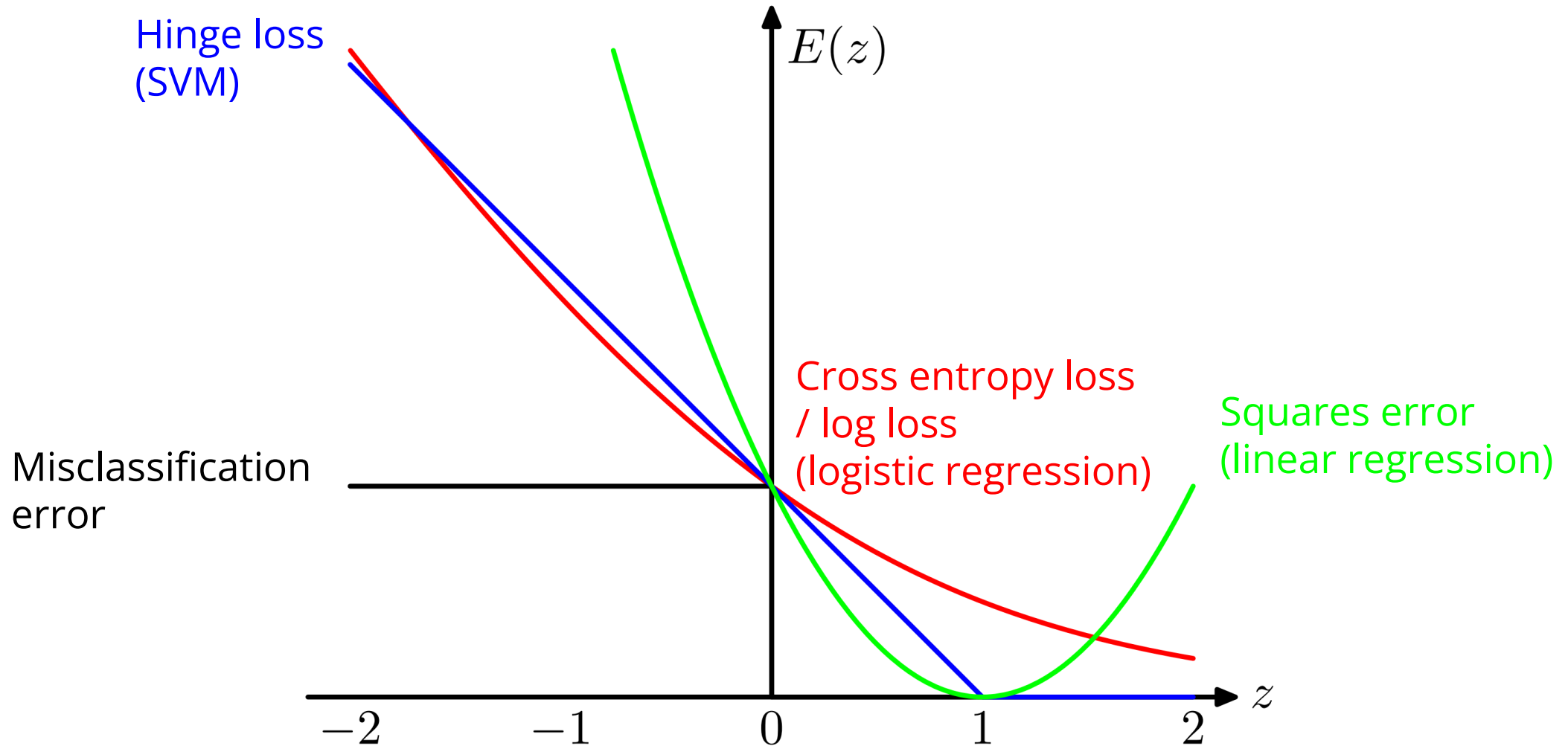
$$\xi_n \geq 0 \quad \forall n$$

$$\operatorname{argmin}_{\mathbf{w}, b} \frac{1}{n} \sum_{n=1}^N \xi_n + \lambda \|\mathbf{w}\|^2 \quad \text{s. t. } \xi_n = \max(0, 1 - t_n(\mathbf{w}^T \mathbf{x}_n + b)) \quad \forall n$$

$$\operatorname{argmin}_{\mathbf{w}, b} \underbrace{\frac{1}{n} \sum_{n=1}^N \max(0, 1 - t_n(\mathbf{w}^T \mathbf{x}_n + b))}_{\text{Hinge loss}} + \lambda \|\mathbf{w}\|^2$$

L2 regularization

SVM, linear regression, logistic regression



Midterm logistics

- Written exam, Wednesday 10/5, in-class
- Closed book. You may bring a single-page letter-sized cheat sheet (with your name on it).
- No computers. Basic calculator allowed.
- Topics:
 - Probability basics
 - MLE vs MAP parameters
 - Discrete / continuous Bayes classifier
 - Naïve Bayes classifier
 - Brief questions about regression and classification algorithms

Homework 1 solutions