CS/ECE/ME 532 Matrix Methods in Machine Learning



Welcome!

The next three weeks...



- This week: finish Unit 5: hinge loss, SVM, stochastic GD
- Next week: start Unit 6: kernel methods
- The week after: finish Unit 6: neural networks + A4 review.
- Tuesday, May 7: Assessment 4

Due dates:

- Tomorrow: Assignment 8
- *Note*: two assignments are due in the last week of classes:
 - Wednesday, May 1: Assignment 9
 - Friday, May 3: Assignment 10

Activity 19



Loss functions

Classifying new data:

features weights
$$\widehat{y} = \operatorname{sign}(\boldsymbol{x}^T \boldsymbol{w})$$

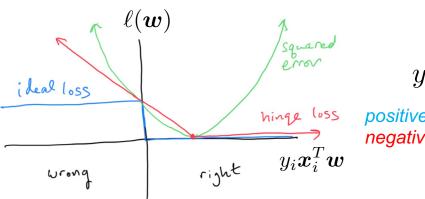
Training a classifier:

$$\min_{oldsymbol{w}} rac{loss\ function}{\ell(oldsymbol{w}) + \lambda r(oldsymbol{w})}$$

• squared error
$$||\boldsymbol{X}\boldsymbol{w} - \boldsymbol{y}||_2^2$$

$$\ell(oldsymbol{w})$$

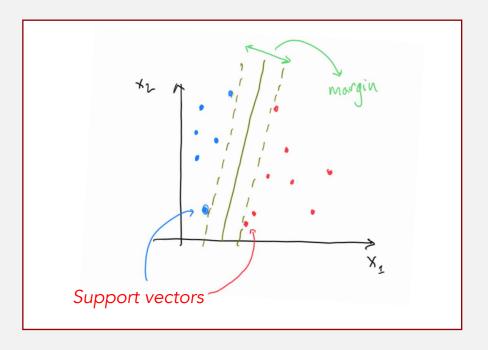
- ideal (0-1) loss $\sum_{i} \frac{1}{2} |y_i \operatorname{sign}(\mathbf{x}_i^T \mathbf{w})|$
- hinge loss $\sum_{i} (1 y_i \boldsymbol{x}_i^T \boldsymbol{w})_+$
- logistic loss $\log(1 + e^{-y_i \boldsymbol{x}_i^T \boldsymbol{w}})$



 $y_i oldsymbol{x}_i^T oldsymbol{w}$

positive when correct negative when wrong

Support Vector Machines



maximize margin s.t. correct classification minimize $||\tilde{\boldsymbol{w}}||^2$ s.t. $y_i \boldsymbol{x}_i^T \boldsymbol{w} \ge 1$ for i = 1, ...

For non-separable data:
$$\min_{\boldsymbol{w}} \sum_{i} (1 - y_i \boldsymbol{x}_i^T \boldsymbol{w})_+ + \lambda ||\tilde{\boldsymbol{w}}||_2^2$$