Unsupervised Learning + Revision

COMP9417, 23T1

1. Unsupervised Learning
2. Revision
3. Gradient Descent Question

Section 1

Unsupervised Learning

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Learning without any labels.

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The content this week is light, so I'll go straight to the lab to explain it.

Section 2

Revision

Identities

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Some general identities which may be useful for this course:

Vector Calculus

If x is an arbitrary vector, and c is any constant (vector or scalar),

$$\frac{\partial(xc)}{\partial x} = c^T \qquad \frac{\partial(x^T cx)}{\partial x} = 2cx$$

The First Question

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Describe Ridge and LASSO regression and how they differ.

Linear Methods

Name this algorithm and what it represents,

$$\begin{aligned}\hat{p} &= \sigma(X\beta) \\ &= \frac{1}{1+e^{-X\beta}}\end{aligned}$$

Dual Perceptron

Recall the primal perceptron:

$converged \leftarrow 0$
while not $converged$ **do**
  $converged \leftarrow 1$
  for $x_i \in X, y_i \in y$ **do**
    if $y_i w \cdot x_i \leq 0$ **then**
      $w \leftarrow w + \eta y_i x_i$
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- What is the **Kernel trick**?
- What problem does the SVM solve?

Ensemble Methods

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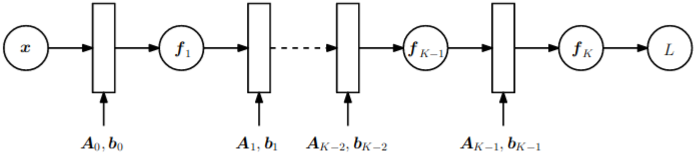
Why does bagging reduce our model's variance?

Neural Learning

Given the following diagram, derive expressions for $\frac{\partial L}{\partial \theta_k}$ for $k = 0, \ldots, K$ where $\theta_k = \{A_k, b_k\}$



Section 3

Gradient Descent Question

Gradient Descent Question

Given $w = (w_0, w_1, w_2, w_3)^T$, $X^{(i)} = (1, x_1^{(i)}, x_2^{(i)}, x_3^{(i)})$ for a model:

$$\hat{y}^i = w_0 + w_1 x_1^{(i)} + w_2 x_2^{(i)} + w_3 x_3^{(i)} \hat{y}^i \qquad = w^T X^{(i)}$$

We define the mean-loss of our model as:

$$L_c(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^{n} L_c(y^{(i)}, \hat{y}^{(i)}) = \frac{1}{n} \sum_{i=1}^{n} \left[\sqrt{\frac{1}{c^2} (y^{(i)} - \langle w^{(t)}, X^{(i)} \rangle)^2 + 1} - 1 \right]$$

Part A

Calculate $\frac{\partial L_c(y,\hat{y})}{\partial w_k}$, where $k = 0, \ldots, 4$.

Part B

Take $c = 2$, what are the GD updates to w for a learning rate η? What are the SGD updates?

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$$w_k^{(t+1)} = w_k^{(t)} - \eta \cdot \frac{1}{n} \sum_{i=1}^{n} \frac{X_k^{(i)}(y_i - \langle w^{(t)}, X^{(i)} \rangle)}{2\sqrt{(y_i - \langle w^{(t)}, X^{(i)} \rangle)^2 + 4}}$$

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For SGD,

$$w_k^{(t+1)} = w_k^{(t)} - \frac{X_k^{(i)}(y_i - \langle w^{(t)}, X^{(i)} \rangle)}{2\sqrt{(y_i - \langle w^{(t)}, X^{(i)} \rangle)^2 + 4}} \qquad \text{for a random } i \in [1, n]$$