

# CSC411 Assignment 3

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## 1 20 News Group

### 1.1 Top 3 Algorithms

#### 1.1.1 Neural Network

1. Hypterparameter

In the code `nn_news`, I have tried a single layer neural network vs multi-layered neural network. It turns out that the single neural network is the fastest and also most accurate.

2. Train/test loss

- Train accuracy
- Test accuracy

3. My expectations

#### 1.1.2 Random forest

1. Hypterparameter

In the code `nn_news`, I have tried a single layer neural network vs multi-layered neural network. It turns out that the single neural network is the fastest and also most accurate.

2. Train/test loss

- Train accuracy
- Test accuracy

3. My expectations

#### 1.1.3 SVM - Best Classifier

1. Hypterparameter

In the code `nn_news`, I have tried a single layer neural network vs multi-layered neural network. It turns out that the single neural network is the fastest and also most accurate.

2. Train/test loss

- Train accuracy 0.972511932119
- Test accuracy 0.691980881572

3. My expectations

#### 1.1.4 Bernoulli Baseline

1. Train/test loss

- Train accuracy 0.598727240587
- Test accuracy 0.457912904939

## 2 SVM

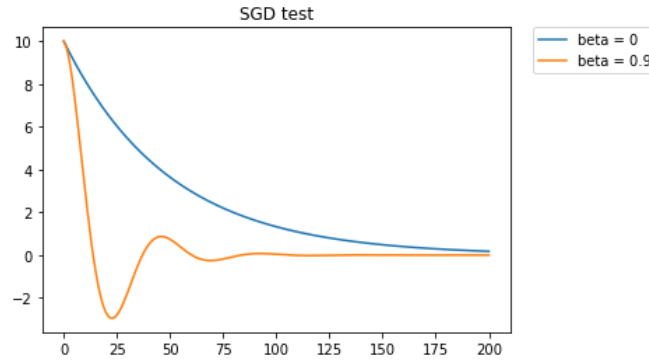


Figure 1: Plot of test SVM

## 3 Kernels

### 3.1 Positive semidefinite and quadratic form

Assume  $K$  is symmetric, we can decompose  $K$  into  $U\Lambda U^T$

$$x^T K x = x^T (U \Lambda U^T) x = (x^T U) \Lambda (U^T x)$$

$\Lambda$  has the eigenvalues  $\lambda_i$ , and if  $K$  is positive, and all  $\lambda_i > 0$ ,

$$x^T K x = \sum_{i=1}^d \lambda_i ([x^T U_i])^2 \geq 0$$

Then  $x^T K x \geq 0$  for all  $x$  in  $\mathbb{R}^d$

### 3.2 Kernel properties

#### 3.2.1 $\alpha$

Define mapping  $\phi(x) = \sqrt{\alpha}$ ,  $\alpha > 0$ , and the kernel  $\langle \phi(x), \phi(y) \rangle = \alpha$ . The resulting matrix  $K$  has item  $K_{ij} = \alpha$ , the matrix  $K$  has equal number of row and columns, and each element is  $\alpha$ . Since  $\alpha > 0$ , and all elements are equal,  $K$  is positive semidefinite

#### 3.2.2 $f(x), f(y)$

$$K_{ij} = \langle \phi(x), \phi(y) \rangle,$$

define  $\phi(x) = f(x), \forall f : \mathbb{R}^d \rightarrow \mathbb{R}$

define  $\phi(y) = f(y), \forall f : \mathbb{R}^d \rightarrow \mathbb{R}$

Since  $f(x)$  and  $f(y)$  produce a scalar,  $\langle \phi(x), \phi(y) \rangle = f(x) \cdot f(y)$

#### 3.2.3 $k_1$ and $k_2$

If the gram matrix,  $K_1$  of kernel  $k_1$  and gram matrix,  $K_2$  of kernel  $k_2$  are positive semidefinite, by scaling them and adding each element, the new gram matrix of  $a \cdot k_1(x, y) + b \cdot k_2(x, y)$ , call it  $K$ , each element of  $K$  is positive since  $a, b > 0$ .

$K$  is also symmetric because  $K_1$  and  $K_2$  are symmetric with the same dimension, and element wise addition and linear combination preserve the symmetric property.

**3.2.4**  $k(x, y) = \frac{k_1(x, y)}{\sqrt{k_1(x, x)}\sqrt{k_1(y, y)}}$

Let  $\phi_1$  be the mapping defined by  $k_1$

We define a new mapping,  $\phi$  for  $k(x, y)$

We let  $\phi(x) = \frac{\phi_1(x)}{\|\phi_1(x)\|}$

$$\begin{aligned}
 k(x, y) &= \langle \phi(x), \phi(y) \rangle \\
 &= \frac{\phi_1(x)}{\|\phi_1(x)\|} \cdot \frac{\phi_1(y)}{\|\phi_1(y)\|} \\
 &= \frac{\phi_1(x)}{\sqrt{\phi_1(x) \cdot \phi_1(x)}} \cdot \frac{\phi_1(y)}{\sqrt{\phi_1(y) \cdot \phi_1(y)}} \\
 &= \frac{\phi_1(x)}{(\sqrt{\phi_1(x)} \cdot \sqrt{\phi_1(y)})} \cdot \frac{\phi_1(y)}{(\sqrt{\phi_1(x)} \cdot \sqrt{\phi_1(y)})} \\
 &= \frac{\phi_1(x)}{\sqrt{\phi_1(x) \cdot \phi_1(y)}} \cdot \frac{\phi_1(y)}{\sqrt{\phi_1(x) \cdot \phi_1(y)}} \\
 k(x, y) &= \frac{k_1(x, y)}{\sqrt{k_1(x, x)}\sqrt{k_1(y, y)}}
 \end{aligned}$$

Therefore, there is a new mapping  $\phi(x)$  that supports  $k(x, y)$  and it is a kernel because  $\phi(x)$  is the product of two kernel mappings