

# **CSC411: Assignment 3**

Due on Sunday, December 3<sup>rd</sup>, 2017

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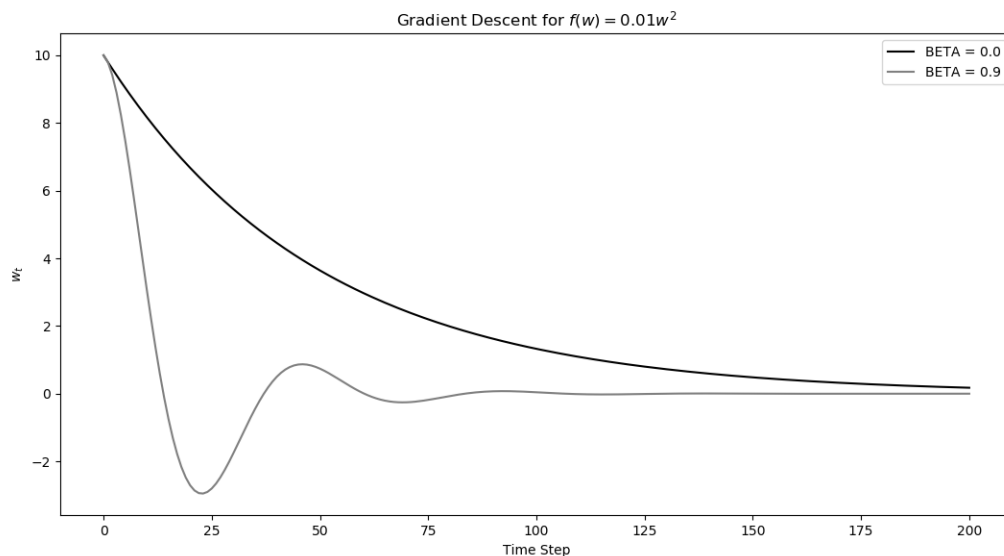
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## 1 - 20 Newsgroup Predictions

## 2 - Training SVM with SGD

### 2.1 - SGD with Momentum

Plotting  $w_t$  for each time step  $t$  by applying the iterative stochastic gradient-descent on  $f(w) = 0.01w^2$ , we get the following graph (for  $\beta = 0.1$  and  $\beta = 0.9$  for upto 200 time-steps):



## 2.2 - Training SVM

## 2.3 - Apply 4-vs-9 Digits on MNIST

### 2.3.1 - Training Loss

### 2.3.2 - Test Loss

### 2.3.3 - Classification Accuracy on the Training Set

### 2.3.4 - Classification Accuracy on the Test Set

### 2.3.5 - Plot $w$ as a $28 \times 28$ image

## 3 - Kernels

### 3.1 - Positive Semi definite and Quadratic Form

Prove that a symmetric matrix  $K \in \mathbb{R}^{d \times d}$  is a positive semi definite iff for all vectors  $x$  we have  $\mathbf{x}^T K \mathbf{x} \geq 0$ .

Proof:

$$K \mathbf{x} = \lambda \mathbf{x}$$

where  $\lambda$  is the eigenvalue and  $\mathbf{x}$  is the eigenvector.

Suppose  $\mathbf{x}$  is an eigenvector of  $K$  and replacing  $K \mathbf{v}$  with  $\lambda \mathbf{v}$  (from the definition of an eigenvector and eigenvalue above):

$$\mathbf{x}^T K \mathbf{x} = \mathbf{x}^T \mathbf{x} \lambda$$

$$\mathbf{x}^T K \mathbf{x} = |\mathbf{x}|^2 \lambda$$

Therefore, as  $|\mathbf{x}|^2 \geq 0$ , for the equation  $\mathbf{x}^T K \mathbf{x} \geq 0$ , the eigenvalue must be:  $\lambda \geq 0$ . Since it is a semi-definite matrix, where the eigenvalues  $\geq 0$ , this holds true.

## 3.2 - Kernel Properties

**3.2.1 - Prove Property**  $k(\mathbf{x}, \mathbf{y}) = \alpha$  is a kernel for  $\alpha > 0$

$$\phi(\mathbf{x}) = \sqrt{\alpha}$$

$$k(\mathbf{x}, \mathbf{y}) = \langle \phi(\mathbf{x}), \phi(\mathbf{y}) \rangle$$

$$k(\mathbf{x}, \mathbf{y}) = \sqrt{\alpha}\sqrt{\alpha}$$

$$k(\mathbf{x}, \mathbf{y}) = \alpha$$

**3.2.2 - Prove Property**  $k(\mathbf{x}, \mathbf{y}) = f(\mathbf{x}) \cdot f(\mathbf{y})$  is a kernel for  $f : \mathbb{R}^d \rightarrow \mathbb{R}$

$$\phi(\mathbf{x}) = f(\mathbf{x})$$

$$k(\mathbf{x}, \mathbf{y}) = \langle \phi(\mathbf{x}), \phi(\mathbf{y}) \rangle$$

$$k(\mathbf{x}, \mathbf{y}) = f(\mathbf{x}) \cdot f(\mathbf{y})$$

**3.2.3 - Prove Property** If  $k_1(\mathbf{x}, \mathbf{y})$  and  $k_2(\mathbf{x}, \mathbf{y})$  are kernels then  $k(\mathbf{x}, \mathbf{y}) = a \cdot k_1(\mathbf{x}, \mathbf{y}) + b \cdot k_2(\mathbf{x}, \mathbf{y})$  for  $a, b > 0$  is a kernel

**3.2.4 - Prove Property**