

# Appendix A

## Definitions

In this chapter, we explain the basic mathematical definitions and concepts that are used in this thesis. Most of the definitions and propositions are taken from [29, 171, 18, 197] that are ready reference used throughout the thesis.

**Vector Space:** A vector space  $V$  is a set that is closed under finite vector-addition and scalar-multiplication. In order for  $V$  to be a vector space, the following conditions must hold for all elements  $X, Y, Z \in V$  and any scalars  $r, s$ :

1. Commutativity ( $X + Y = Y + X$ )
2. Associativity of vector addition ( $(X + Y) + Z = X + (Y + Z)$ )
3. Additive identity ( For all  $X$ ,  $0 + X = X + 0 = X$ )
4. Existence of additive inverse (For any  $X$ , there exists a  $-X$  such that  $(X + (-X) = 0)$ )
5. Associativity of scalar multiplication ( $r(sX) = (rs)X$ )
6. Distributivity of scalar sums ( $(r + s)X = rX + sX$ )
7. Distributivity of vector sums ( $r(X + Y) = rX + rY$ )
8. Scalar multiplication identity ( $1X = X$ )

**Metric Space:** A set  $S$  with a global distance function  $d$  that, for every two points  $x, y \in S$ , gives the distance between them as a nonnegative real number  $g(x, y)$ . A metric space must also satisfy

1.  $g(x, y) = 0$  iff  $x = y$ ,
2.  $g(x, y) = g(y, x)$ ,
3. The triangle inequality  $g(x, y) + g(y, z) \geq g(x, z)$ .

**Cauchy Sequence:** A sequence  $x_1, x_2, \dots$  such that the metric  $d(x_m, x_n)$  satisfies

$$\lim_{(m,n) \rightarrow \infty} d(x_m, x_n) = 0.$$

**Complete Metric Space:** A metric space in which every Cauchy sequence is convergent.

**Norm:** A norm  $\|\cdot\|$  on  $\mathbb{R}^n$  is a function that assigns a scalar  $\|x\|$  to every  $x \in \mathbb{R}^n$  and that has the following properties:

- (a)  $\|x\| \geq 0, \forall x \in \mathbb{R}^n$ .
- (b)  $\|\alpha x\| = \alpha \cdot \|x\|$  for every scalar  $\alpha$  and every  $x \in \mathbb{R}^n$ .
- (c)  $\|x\| = 0$  if and only if  $x = 0$ .
- (d)  $\|x + y\| \leq \|x\| + \|y\|, \forall x, y \in \mathbb{R}^n$  (the triangle inequality).

**Banach Spaces:** Any convergent sequence in a normed linear space is a Cauchy sequence. However, it may or may not be true in an arbitrary normed linear space that all Cauchy sequences are convergent. A normed linear space  $X$  which has the property that all Cauchy sequences are convergent is said to be complete. A complete normed linear space is called a Banach space.

**Hilbert Space:** A linear space  $\mathcal{H}$  with an inner product  $\langle \cdot, \cdot \rangle$ , which is complete with respect to the norm  $\|x\| = \sqrt{\langle x, x \rangle}$  induced by this inner product is called a Hilbert space. Hilbert space is considered to be the generalized Euclidean space with infinite dimensions.

**Proposition A.1.** [29] *Every bounded and monotonically non-increasing or non-decreasing scalar sequence converges.*

**Closed and Open sets:** We say that  $x$  is a closure point of a subset  $X$  of  $\mathbb{R}^n$  if there exists a sequence  $\{x_n\} \in X$  that converges to  $x$ .  $X$  is called closed if it is equal to its closure. It is called open if its complement,  $\{x \mid x \notin X\}$ , is closed. It is called bounded if there exists a scalar  $c$  such that  $\|x\| \leq c$  for all  $x \in X$ . It is called compact if it is closed and bounded.

For any  $\varepsilon > 0$  and  $x^* \in \mathbb{R}^n$ ,

- $\{x \mid \|x - x^*\| < \varepsilon\}$  is open and is called an open sphere centered at  $x^*$ .

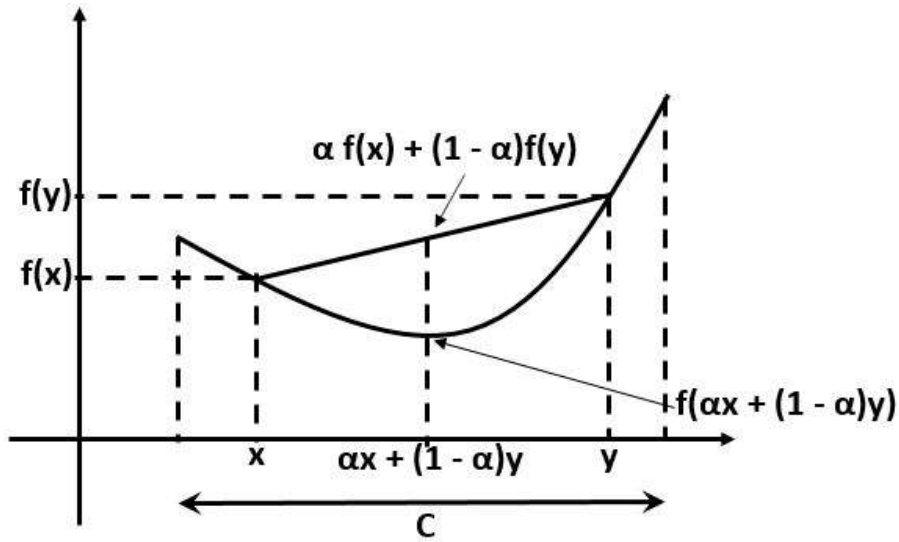


FIGURE A.1: Illustration of convex functions.

- $\{x \mid \|x - x^*\| \leq \varepsilon\}$  is open and is called an open sphere centered at  $x^*$ .

**Convex Set:** A subset  $C$  of  $\mathbb{R}^n$  is called *convex*, if

$$\alpha x + (1 - \alpha)y \in C, \quad \forall x, y \in C, \forall \alpha \in [0, 1].$$

**Convex Functions:** Let  $C$  be a convex subset of  $\mathbb{R}^n$ . A function  $f : C \rightarrow \mathbb{R}$  is called convex if

$$f(\alpha x + (1 - \alpha)y) \leq \alpha f(x) + (1 - \alpha)f(y), \quad \forall x, y \in C, \forall \alpha \in [0, 1].$$

Figure A.1 demonstrate the convex functions.

**Operators:** Also called relations or multi-valued functions, an operator  $T$  is on  $\mathbb{R}^n$  is a subset of  $\mathbb{R}^n \times \mathbb{R}^n$ .

**Subdifferential:** The subdifferential relation  $\partial f$  of a function  $f : \mathbb{R} \rightarrow \mathbb{R} \cup \infty$ , defined by

$$\partial f = (x, g) \mid x \in C, \forall z \in \mathbb{R}^n, f(z) \geq f(x) + g^T(z - x)$$

The set  $\partial f(x)$  is the subdifferential of  $f$  at  $x$ . Any  $g \in \partial f(x)$  is called a subgradient of  $f$  at  $x$ .

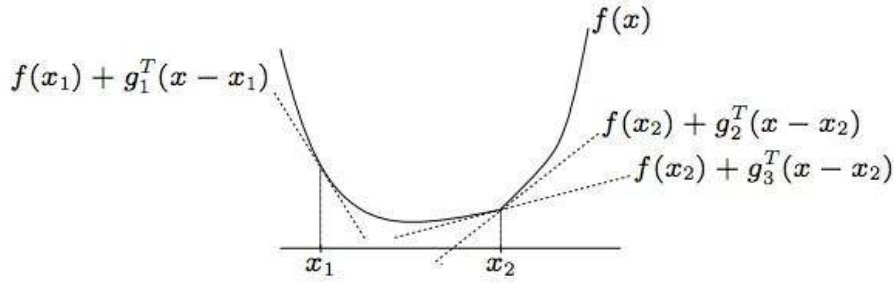


FIGURE A.2: Illustration of Subdifferential [197]

**Zeros of an Operator:** When  $T \ni 0$ , we say that  $x$  is a zero of  $T$ .

**Monotone Operators:** We say that an operator  $T : \mathcal{H} \rightarrow \mathcal{H}$  is:

1. monotone if,

$$\langle Tx - Ty, x - y \rangle \geq \eta \|x - y\|^2,$$

for a constant  $\eta \geq 0$  and for all  $x, y \in X$ . If  $\eta > 0$ , then we say that  $T$  is strongly monotone or  $\eta$ -strongly monotone.

2. It is  $\delta$ -cocoercive if  $\delta T$  is firmly non-expansive, i.e.,

$$\langle Tx - Ty, x - y \rangle \geq \delta \|Tx - Ty\|^2.$$

3. It is an  $L$ -Lipschitz operator if there exists  $L \in [0, \infty)$  such that

$$\|Tx - Ty\| \leq L \|x - y\|, \quad x, y \in \mathcal{H}.$$

It is nonexpansive if it is Lipschitz continuous with constant  $L = 1$ , i.e.,

$$\|Tx - Ty\| \leq \|x - y\|.$$

It is contraction for  $L < 1$ .

4. It is a  $\kappa$ -strict pseudo-contraction if for a constant  $\kappa \in [0, 1)$ ,

$$\|Tx - Ty\|^2 \leq \|x - y\|^2 + \kappa \|(I - T)x - (I - T)y\|^2.$$

It is said to be pseudo-contractive if  $\kappa = 1$ .

Let  $X$  be a subset of a Hilbert space  $\mathcal{H}$ . A mapping  $T : X \rightarrow X$  is said to be asymptotically nonexpansive if there exists a sequence  $\{k_i\}$  of real numbers with  $k_i \rightarrow 1$  as  $i \rightarrow \infty$ , such that,

$$\|T^i x - T^i y\| \leq k_i \|x - y\|, \quad x, y \in X.$$

Note: Mapping a pair of points by a contraction reduces the distance between them; mapping them by a nonexpansive operator does not increase the distance between them.

**Norms:** A norm is a function that assigns a strictly positive length or size to each vector in a vector space.

$$\|x\|_p = \begin{cases} (|x_1|^p + \cdots + |x_n|^p)^{\frac{1}{p}}, & \text{if } 1 \leq p < \infty \\ \max(|x_1|, \dots, |x_n|), & \text{if } p = \infty \end{cases}$$

**Fixed-point Iterations:** A fixed point of a function  $f$  is a number  $x^*$  such that  $x^* = f(x^*)$ , in other words, it is a solution of the equation  $x = f(x)$ . The iteration  $x_{n+1} \leftarrow f(x_n)$  for  $n = 0, 1, \dots$  is called fixed point iteration.

Note: Assume that  $f(x)$  is a continuous function and that  $\{x_n\}_{n=0}^{\infty}$  is a sequence generated by fixed point iteration. If  $\lim_{n \rightarrow \infty} x_n = x^*$ , then  $x^*$  is a fixed point of  $f(x)$ .

**Weak Convergence:** A sequence of points  $\{x_n\}$  in a Hilbert space  $\mathcal{H}$  is said to converge weakly to a point  $x \in \mathcal{H}$  if,

$$\langle x_n, y \rangle \rightarrow \langle x, y \rangle, \quad \forall y \in \mathcal{H}.$$

**Strong Convergence:** A sequence of points  $\{x_n\}$  in a Hilbert space  $\mathcal{H}$  is said to converge strongly to a point  $x \in \mathcal{H}$  if,

$$\|x_n - x\| \rightarrow 0 \text{ as } n \rightarrow \infty.$$

**Maximal Monotone Operator:** Operator  $T$  is maximal monotone operator, if the graph  $G(T)$  is not properly contained in the graph of any other monotone operator. An example of maximal monotone operator is the sub-differential of a convex function.

For any  $c > 0$ , the resolvent  $J_c^T$  defined as  $J_c^T = (I + cT)^{-1}$  of a maximal monotone operator  $T$  is a non-expansive operator. It is well-known that for any  $\lambda > 0$ , the resolvent of a maximal monotone operator  $T$  is a non-expansive operator [167].

# Appendix B

## List of Publications

### Journals

1. Mridula Verma and K K Shukla (2017) A New Accelerated Proximal Technique for Regression with High-dimensional Datasets. **Knowledge and Information Systems (KAIS)**, doi: 10.1007/s10115-017-1047-z, (**Acceptance Rate < 19.1%**), **Impact Factor: 2.004**.
2. Mridula Verma, K.K. Shukla (2017) A new accelerated proximal gradient technique for regularized multitask learning framework, Pattern Recognition Letters, Volume 95, 2017, Pages 98-103, ISSN 0167-8655, <http://dx.doi.org/10.1016/j.patrec.2017.06.013>. **Impact Factor: 1.995**.
3. Mridula Verma, D R Sahu and K K Shukla (2017) VAGA: A Novel Viscosity-based Accelerated Gradient Algorithm: Convergence Analysis and Application to Multitask Regression. **Applied Intelligence**, under minor revision, **Impact Factor: 1.904**.
4. Mridula Verma and K K Shukla (2017) An Extragradient-based Accelerated Algorithm for Microarray Gene Analysis. **Data Mining and Knowledge Discovery**, under review.
5. Mridula Verma and K K Shukla (2017) A New Operator Splitting Algorithm and its Accelerated Variant with Application to Microarray Gene Analysis, **IEEE Transactions on Computational Biology and Bioinformatics**. Communicated.

## Conferences

1. Mridula Verma and K K Shukla (2017) Fast Multi-Modal Unified Sparse Representation Learning. Proceedings of 17<sup>th</sup> **ACM International Conference on Multimedia Retrieval**, June 2017. (**Conference Ranked #1 in the field of Multimedia Retrieval**), Bucharest, Romania (**acceptance rate: 37%**).
2. Mridula Verma, Prayas Jain, K K Shukla (2016), A New Faster First Order Iterative Scheme for Sparsity-based Multitask Learning, Proceedings of 2016 **IEEE International Conference on Systems, Man, and Cybernetics (SMC)**, Budapest, Hungary, pp. 1603-1608.
3. Mridula Verma, K K Shukla (2016), Performance Comparison of Proximal Methods for Regression with Nonsmooth Regularizers on Real Datasets, Proceedings of Fifth **International Conference on Computing, Communications and Informatics (ICACCI-2016)**, Jaipur. (**Acceptance Rate: 23%**)
4. Mridula Verma, K K Shukla (2016), Efficient Kernel Fuzzy c-means Clustering on Very Large Scale Data using Random Fourier Features, Proceedings of **International Conference on Emerging Research in Computing, Information, Communication and Applications (ERCICA-14)**, Elsevier, Bangalore. (**Acceptance Rate: 33%**)