

# Tutorial 3: Dimensionality Reduction

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# Outline

- 1 Lagrange Optimization
- 2 Generalized Rayleigh Quotient
- 3 Exercises

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# 1. Lagrange Optimization

Constrained optimization problem:

$$\max_{\mathbf{x}} f(\mathbf{x}), \quad (1)$$

$$s.t. \quad g(\mathbf{x}) = 0. \quad (2)$$

The solution can often be found by Lagrangian method. The Lagrangian is defined as:

$$L(\mathbf{x}, \lambda) = f(\mathbf{x}) + \lambda g(\mathbf{x}). \quad (3)$$

# 1. Lagrange Optimization

**Lagrangian Sufficiency Theorem:** Suppose there exist  $\mathbf{x}^* \in \mathbf{X}$  and  $\lambda^*$ , such that  $\mathbf{x}^*$  maximize  $L(\mathbf{x}, \lambda^*)$  over all  $\mathbf{x} \in \mathbf{X}$ , and  $g(\mathbf{x}^*) = 0$ . Then  $\mathbf{x}^*$  solves the optimization problem.

**Proof.**

$$\max_{\mathbf{x} \in \mathbf{X}, g(\mathbf{x})=0} f(\mathbf{x}) \quad (4)$$

$$= \max_{\mathbf{x} \in \mathbf{X}, g(\mathbf{x})=0} [f(\mathbf{x}) + \lambda^* g(\mathbf{x})] \quad (5)$$

$$\leq \max_{\mathbf{x} \in \mathbf{X}} [f(\mathbf{x}) + \lambda^* g(\mathbf{x})] \quad (6)$$

$$= [f(\mathbf{x}^*) + \lambda^* g(\mathbf{x}^*)] \quad (7)$$

$$= f(\mathbf{x}^*) \quad (8)$$

# 1. Lagrange Optimization

**Solve Lagrange Optimization:** solve the unconstrained problem by taking the derivative w.r.t.  $\mathbf{x}$  and  $\lambda$ :

$$\frac{\partial L(\mathbf{x}, \lambda)}{\partial \mathbf{x}} = \frac{\partial f(\mathbf{x})}{\partial \mathbf{x}} + \lambda \frac{\partial g(\mathbf{x})}{\partial \mathbf{x}} = 0 \quad (9)$$

$$\frac{\partial L(\mathbf{x}, \lambda)}{\partial \lambda} = 0 \quad (10)$$

$$g(\mathbf{x}) = 0 \quad (11)$$

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## 2. Generalized Rayleigh Quotient

### Fisher Criterion

$$J(\mathbf{w}) = \frac{\mathbf{w}^t \mathbf{S}_B \mathbf{w}}{\mathbf{w}^t \mathbf{S}_W \mathbf{w}} \quad (12)$$

$J(\mathbf{w})$  is the generalized Rayleigh quotient. A vector  $\mathbf{w}$  that maximizes  $J(\cdot)$  must satisfy

$$\mathbf{S}_B \mathbf{w} = \lambda \mathbf{S}_W \mathbf{w} \quad (13)$$

for some constant  $\lambda$ .

## 2. Generalized Rayleigh Quotient

Maximizing  $J(\mathbf{w})$  is equivalent to

$$\max_{\mathbf{w}} \quad \mathbf{w}^t \mathbf{S}_B \mathbf{w} \quad (14)$$

$$s.t. \quad \mathbf{w}^t \mathbf{S}_W \mathbf{w} = K \quad (15)$$

which can be solved using Lagrange multipliers.

## 2. Generalized Rayleigh Quotient

Define the Lagrangian:

$$L = \mathbf{w}^t \mathbf{S}_B \mathbf{w} - \lambda(\mathbf{w}^t \mathbf{S}_W \mathbf{w} - K) \quad (16)$$

Maximize with respect to  $\mathbf{w}$ :

$$\nabla_{\mathbf{w}} L = 2(\mathbf{S}_B - \lambda \mathbf{S}_W) \mathbf{w} = 0 \quad (17)$$

To obtain the solution:

$$\mathbf{S}_B \mathbf{w} = \lambda \mathbf{S}_W \mathbf{w} \quad (18)$$

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