

# Low Rank Functional Analysis-of-Variance Modeling

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# Overview

- Background
- Model Introduction
- Fitting Method
- Sub-problem Fitting Algorithms
- Preliminary Numerical Results
- Future Work

# Background

- Additive Model(Stone, 1986)

$y_i$  is a response and  $p$ -dimensional covariate vector  $x_i = (x_{i1}, \dots, x_{ip})$

$$y_i = \mu + \sum_{j=1}^p f_j(x_{ij}) + \epsilon_i$$

- Functional analysis of variance (ANOVA) modeling

$$Y_i = \mu + \sum_{1 \leq j \leq p} f_j(x_{ij}) + \sum_{1 \leq j_1 \leq j_2} f_{j_1, j_2}(x_{ij_1}, x_{ij_2}) + \dots + \sum_{1 \leq j_1 \leq \dots \leq j_K \leq p} f_{j_1, \dots, j_K}(x_{ij_1}, \dots, x_{ij_K}) + \epsilon_i$$

# Background

## Problem of Increasing Dimensionality

Basic:  $\phi_{j_k}^m(x_{j_k}) \quad m = 1, \dots, p$

$$f_{j_1, \dots, j_K}(x_{ij_1}, \dots, x_{ij_K}) = \sum_{1 \leq m_1 \leq \dots \leq m_K \leq p} \beta_{m_1, \dots, m_K} \prod_{k=1}^K \phi_{j_k}^{m_k}(x_{j_k})$$

$$|\{\beta_{m_1, \dots, m_K}\}| = p^K.$$

# Model Introduction

- Low Rank ANOVA modeling(Suppose we have 3 variables  $x_1, x_2, x_3$ )

$$Y_i = \mu + \sum_{j=1}^3 f_j(x_{ij}) + f_1^{(1,2)}(x_{i1})f_2^{(1,2)}(x_{i2}) + f_1^{(1,3)}(x_{i1})f_3^{(1,3)}(x_{i3}) + f_2^{(2,3)}(x_{i2})f_3^{(2,3)}(x_{i3}) \\ + f_1^{(1,2,3)}(x_{i1})f_2^{(1,2,3)}(x_{i2})f_3^{(1,2,3)}(x_{i3})$$

## Dimensionality

$$\phi_{j_k}^m(x_{j_k}), \quad m = 1, \dots, p$$

$$\prod_{k=1}^3 f_k^{(1,2,3)}(x_{ik}) = \sum_{1 \leq m_1 \leq \dots \leq m_K \leq p} \prod_{k=1}^3 \beta_{m_k} \phi_{j_k}^{m_k}(x_{j_k})$$

$$|\{\beta_{m_k}\}| = p * 3$$

# Model Introduction

- Penalty
  - Total Variation:  $TV(f^{(m-1)})$
  - Empirical Norm:  $\|f\|_n = \sqrt{\frac{\sum_{i=1}^n f^2(x_i)}{n}}$

Truncated Power Basics:

$$\phi_k(x) = x^k, k = 1, 2, \dots, m-1, \quad \phi_k(x) = (z - t_{(j)})_+^{(m-1)}, \forall j = 1, \dots, p - m + 1$$

$\Phi_j = (\phi_{1j}, \dots, \phi_{pj}) \in \mathcal{R}^{n \times p}$ ,  $f_j(x_j) = \Phi_j \beta_j \in \mathcal{R}^n$ . and

$$TV(f_j^{(m-1)}) = \|D\beta_j\|_1$$

and

$$\|f_j\|_n = \frac{1}{\sqrt{n}} \|\Phi_j \beta_j\|_2$$

# Model Fitting

$$Y = \mu + \sum_{j=1}^3 (\Phi_j \beta_j) + \sum_{1 \leq j_1 \leq j_2 \leq 3} (\Phi_{j_1} \beta_{j_1}^{(j_1, j_2)}) * (\Phi_{j_2} \beta_{j_2}^{(j_1, j_2)}) + (\Phi_{j_1} \beta_1^{(1,2,3)}) * (\Phi_{j_2} \beta_2^{(1,2,3)}) * (\Phi_{j_3} \beta_3^{(1,2,3)}) + \epsilon_i$$

where  $\Phi_j, \Phi_{j_k} \in \mathbb{R}^{n \times p}$ .  $*$  represent the Hadamard product

$$\begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix} * \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{pmatrix} = \begin{pmatrix} a_1 b_1 \\ a_2 b_2 \\ \vdots \\ a_n b_n \end{pmatrix}$$

Squared loss:

$$\|Y - (\mu + \sum_{j=1}^3 (\Phi_j \beta_j) + \sum_{1 \leq j_1 \leq j_2 \leq 3} (\Phi_{j_1} \beta_{j_1}^{(j_1, j_2)}) * (\Phi_{j_2} \beta_{j_2}^{(j_1, j_2)}) + (\Phi_{j_1} \beta_1^{(1,2,3)}) * (\Phi_{j_2} \beta_2^{(1,2,3)}) * (\Phi_{j_3} \beta_3^{(1,2,3)}))\|^2$$

# Model Fitting

With truncated power basic, if we fixed others parameters and try to update a specific component, such as  $\beta_1^{(12)}$ , then we are trying to solve the following subproblem.

$$\frac{1}{2} \| \text{Residual} - (\text{Diag}(\Phi \beta_2^{(1,2)}) \Phi_1) \beta \|^2 + \rho \| D\beta \|_1 + \lambda \frac{1}{\sqrt{n}} \| \Phi_1 \beta \|_2 \quad (1)$$

is convex w.r.t.  $\beta$ .

Initialization:  $\beta_1, \beta_2, \dots, \beta_1^{(123)}, \dots, \beta_3^{(123)}$

**while** *Not converge* **do**

1. Iteratively choosing a component  $\beta$  from  $\{\beta_1, \beta_2, \dots, \beta_1^{(123)}, \dots, \beta_3^{(123)}\}$
2. Fixed other parameters except  $\beta$ , then minimize the objective function w.r.t.  $\beta$  by solving problem that is similar as (1).

**end**



# Sub-problem Fitting Algorithms

Objective function:

$$\frac{1}{2} \|Y - Kx\|^2 + \rho \|Dx\|_1 + \lambda \|Mx\|_2 \quad (2)$$

**Chambolle-Pock(2010)**

$$G(x) + H(Lx) \quad (3)$$

where  $x \in \mathcal{R}^n$  and  $L \in \mathcal{R}^{m \times n}$

**Conjugated version:**

$$G(x) + \langle y, Lx \rangle - H^*(y) \quad (4)$$

where  $H^*(y) = \min_x \langle y, x \rangle - H(x)$

$(x^*, y^*)$  is a minimizer of (3) iff  $(x^*, y^*)$  is a saddle point of (4).

# Sub-problem Fitting Algorithms

Initialization:  $x_0 \in \mathcal{R}^n, y_0 \in \mathcal{R}^{n \times m}, t=0, \tau, \sigma > 0$

**while** *Not converge* **do**

1.  $x_{t+1} = \text{prox}_{\tau G}(x_t - \tau L^T y_t)$
2.  $y_{t+1} = \text{prox}_{\sigma H^*}(y_t + \sigma(2Lx_{t+1} - Lx_t))$

**end**

**Algorithm 1:** Chambolle-Pock

where proximal operator:  $\text{Prox}_{\sigma F}(x) = \text{argmin}_a F(a) + \frac{1}{2\sigma} \|a - x\|^2$ .

Let  $L = \begin{pmatrix} K \\ M \end{pmatrix} \in \mathcal{R}^{2m \times n}$  and  $G(x) = \rho \|Dx\|_1, H(Lx) = \frac{1}{2} \|Y - Kx\|^2 + \lambda \|Mx\|_2$ .

1.  $x_{t+1} = \text{argmin}_x \frac{1}{2\tau} \|x - (x_t - \tau L^T y_t)\|^2 + \rho \|Dx\|_1$

2.  $y_{t+1} = \begin{pmatrix} \frac{-Y}{\frac{1}{1+1/\sigma} + \frac{1/\sigma y_{1t}}{1+1/\sigma}} \\ \text{Proj}(y_{2t}, \lambda) \end{pmatrix}$

Where  $\text{Proj}(x, \lambda)$  means project  $x$  on spherical  $B(0, \lambda)$ .

# Preliminary Numerical Result

$$Y_i = \mu + \sum_{j=1}^3 f_j(x_{ij}) + \sum_{1 \leq j_1 \leq j_2 \leq 3} f_{j_1}^{(j_1, j_2)}(x_{ij_1}) f_{j_2}^{(j_1, j_2)}(x_{ij_2}) + \epsilon_i \quad (5)$$

Sample size  $n = 500$ .

The true functional components: Truncated Power Basic; Knots=3 or 4,  $m=2$ .

Probability for parameters is set as zero: 0.2

Noise Level:  $SD[Y]*0.05$

Model 1:

$$y_i = \mu + \sum_{j=1}^3 (\Phi_{ij} \beta_j) + \sum_{1 \leq j_1 \leq j_2 \leq 3} (\Phi_{ij_1} \beta_{j_1}^{(j_1, j_2)}) * (\Phi_{ij_2} \beta_{j_2}^{(j_1, j_2)}) + \epsilon_i$$

With total variation of the  $m-1$  order derivation penalty.

Model 2:

$$y_i = \mu + \sum_{j=1}^3 (\Phi_{ij} \beta_j) + \sum_{1 \leq j_1 \leq j_2 \leq 3} \Phi_{i, (j_1, j_2)} \beta_{(j_1, j_2)} + \epsilon_i$$

where  $\Phi_{i, (j_1, j_2)} \in \mathbb{R}^{1 \times p^2}$ . With lasso penalty.

# Preliminary Numerical Result

Estimate Error:  $\sum_{j=1}^3 \|\beta_j - \beta_j^{true}\|^2 + \sum_{1 \leq j_1, j_2 \leq 3} \|\beta_{(j_1, j_2)} - \beta_{(j_1, j_2)}^{true}\|^2$

where  $\beta_{(j_1, j_2)}^{true} = \beta_{j_1}^{(j_1, j_2) true} \diamond \beta_{j_2}^{(j_1, j_2) true} \in \mathbb{R}^{p \times p}$

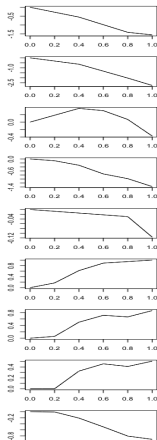
And  $\beta_{(j_1, j_2)} = \beta_{j_1}^{(j_1, j_2)} \diamond \beta_{j_2}^{(j_1, j_2)} \in \mathbb{R}^{p \times p}$  for low rank model.

Error:Mean(SD)	3 knots	4 knots
Low rank model(Repeat 10 times)	0.761(0.409)	22.277(4.513)
Full Model	0.978	43.256

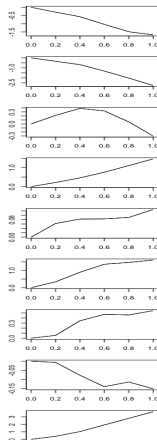
Table: Estimate Error comparison

# Preliminary Numerical Result

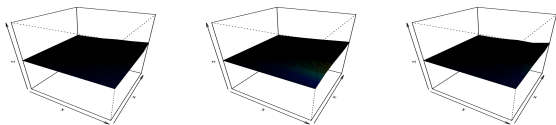
Number of Knots = 4, Estimate Error is around the medium in the 10 times repetition.



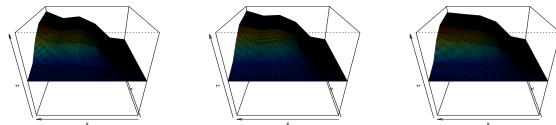
(a) True Components



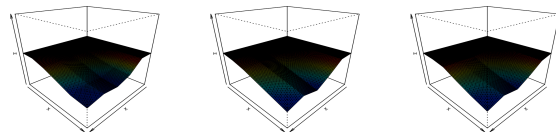
(b) Output Component (Low rank)



(a)  $x_1$  and  $x_2$



(b)  $x_1$  and  $x_3$



(c)  $x_2$  and  $x_3$

Figure: Compare of Interaction effect(From right to left: True, Low rank output, Full model output)

# Future Work

- Improve the fitting algorithm
- Theoretical analysis of the model
- Extended from Rank-1 to Rank-R

$$f_1(x_1)f_2(x_2) \Rightarrow \sum_{r=1}^R f_1^r(x_1)f_2^r(x_2)$$