

High-dimensional Mixed Linear Regression

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Overview

1 Problem Setting

2 Algorithm

3 Simulation

- Symmetric case
- Different Proportion
- Low-dimensional case
- High-dimensional case

Problem Setting : High-dimensional Mixed Linear Regression

- $y_i = \langle x_i, \beta_1^* \rangle z_i + \langle x_i, \beta_2^* \rangle (1 - z_i) + w_i$ for $i = 1, \dots, n$
- $x_i, \beta_i^* \in \mathbb{R}^d, z_i \in \{0, 1\}, w_i \stackrel{iid}{\sim} \mathcal{N}(0, \sigma^2)$
- $d \gg n, \beta_k^*$ is sparse
- **Goal:** infer β_1^*, β_2^* given $\{(x_i, y_i)\}$

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Algorithm 1: Fixed Threshold

Input: $\{(x_i, y_i)\}_{i=1,2,\dots,n}$, $\beta^{(0)}$, T , G , s , $\alpha(< 0.5)$, η

- 1: **for** $t = 1$ to T **do**
 - 2: $J \leftarrow \emptyset$
 - 3: $J \leftarrow$ the smallest (αn) index of $|y_i - \langle x_i, \beta^{(t)} \rangle|$
 - 4: $\beta^{(t+1)} \leftarrow \text{Update}(X, Y, \beta^{(t)}, J, \eta, s, G)$
 - 5: **end for**
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Algorithm 2: Reduced Threshold

Input: $\{(x_i, y_i)\}_{i=1,2,\dots,n}$, $\beta^{(0)}$, T , G , s , $\alpha(< 0.5)$, η , K

- 1: **for** $t = 1$ to T **do**
 - 2: $J \leftarrow \emptyset$
 - 3: $J \leftarrow$ the smallest $\max\{(n - (t - 1)K), n\alpha\}$ index of $|y_i - \langle x_i, \beta^{(t)} \rangle|$
 - 4: $\beta^{(t+1)} \leftarrow \text{Update}(X, Y, \beta^{(t)}, J, \eta, s, G)$
 - 5: **end for**
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Algorithm 3: Reduced Threshold for Mixed Linear Regression

Input: Initial $\beta^{(0)}$, T , G , s , C , $\{(x_i, y_i)\}_{i=1,2,\dots,n}$

- 1: $\beta_1, S_1 \leftarrow \text{Threshold}(X, Y, \beta^{(0)}, T, G, s, \alpha, \eta, K)$
 - 2: $\beta_2, S_2 \leftarrow \text{Robust Regression}(X, Y, \beta^{(0)}, [n] \setminus S_1)$
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1 Problem Setting

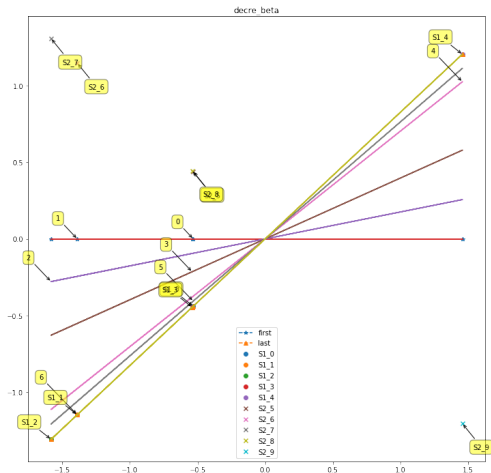
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Symmetric case - x symmetric

$$y_1 = X\beta + e_1, y_2 = -X\beta + e_2$$

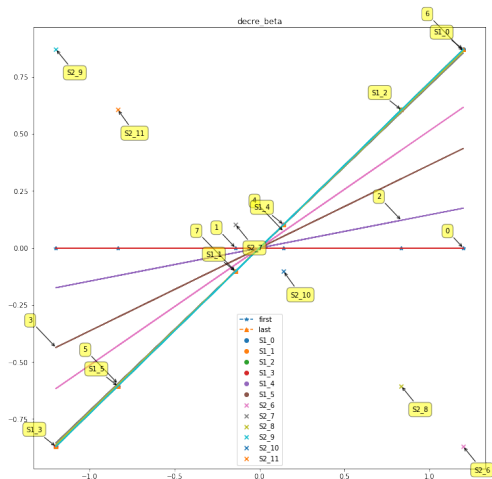


(n, d, σ)	(10,1,0)
Fixed	(5.551e-17 0.05205)
Reduced	(2.776e-17, 4.636e-17)
EM-init	(2.775e-17, 4.635e-17)
EM-rand	(5.551e-17, 0.03268)

Table: (median,mean) over 100 trials(MLR)

Symmetric case - xy symmetric

$$y_1 = X\beta + e_1, y_2 = -X\beta + e_2$$



(n, d, σ)	(10,1,0)
Fixed	(5.551e-17, 0.03604)
Reduced	(2.775e-17, 4.561e-17)
EM-init	(2.775e-17, 4.561e-17)
EM-rand	(1.110e-16, 0.03049)

Table: (median,mean) over 100 trials(MLR)

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Simulation Results - Different Proportion

(n, d, p, σ)	(1000,100,0.1,0)	(1000,100,0.2,0)	(1000,100,0.4,0)
Fixed	(3.968e-12, 4.018e-12)	(4.524e-12, 4.510e-12)	(5.911e-12, 5.8789e-12)
Reduced	(5.590e-12, 5.643e-12)	(6.675e-12, 6.680e-12)	(1.253e-11, 1.269e-11)
EM-init	(0.03459, 0.05530)	(2.638e-17, 0.02041)	(4.579e-16, 0.01127)
EM-rand	(0.1154, 0.1454)	(0.1347, 0.1993)	(0.7476, 0.6216)

(median, mean) over 100 trials (MLR) - Grad Descent (noiseless)

(n, d, p, σ)	(1000,100,0.1,0.1)	(1000,100,0.2,0.1)	(1000,100,0.4,0.1)
Fixed	(0.03837, 0.03855)	(0.04461, 0.04458)	(0.06472, 0.06469)
Reduced	(0.08775, 0.08739)	(0.09009, 0.09031)	(0.09249, 0.09317)
EM-init	(0.09129, 0.1139)	(0.04210, 0.06023)	(0.04899, 0.06161)
EM-rand	(0.1565, 0.1791)	(0.2497, 0.2875)	(0.7080, 0.6076)

(n, d, p, σ)	(1000,100,0.1,0.3)	(1000,100,0.2,0.3)	(1000,100,0.4,0.3)
Fixed	(0.1267, 0.1267)	(0.1536, 0.1548)	(0.3721, 0.3881)
Reduced	(0.2615, 0.2623)	(0.2762, 0.2760)	(0.3098, 0.3118)
EM-init	(0.1930, 0.2186)	(0.1948, 0.2207)	(0.1853, 0.2008)
EM-rand	(0.3327, 0.3537)	(0.5340, 0.5139)	(0.8175, 0.7589)

(median, mean) over 100 trials (MLR) - Grad Descent (noisy)

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Simulation Results - Low-dimensional case

$$y_i = x_i^T \beta_{z_i} + e_i, e_i \sim \mathcal{N}(0, \sigma^2)$$

(n, d, σ)	(30,3,0)	(60,3,0)	(90,3,0)
Fixed	(0.0620,0.246)	(5.207e-16,0.133)	(5.17e-16,0.100)
Reduced	(4.48e-16, 0.0242)	(4.80e-16,6.52e-16)	(4.25e-16,6.33e-16)
EM-init	(3.50e-16,0.0527)	(3.38e-16,0.00596)	(3.33e-16,0.0193)
EM-rand	(3.90e-16,0.167)	(3.68e-16,0.0754)	(3.4e-16,0.0648)

(n, d, s, σ)	(50,5,0)	(100,5,0)	(150,5,0)
Fixed	(0.340,0.347)	(7.15e-16,0.128)	(7.12e-16,0.0308)
Reduced	(7.91e-16,0.0258)	(6.76e-16,9.11e-16)	(6.74e-16,1.02e-15)
EM-init	(6.32e-16,0.0831)	(5.40e-16,0.0184)	(5.13e-16,0.0118)
EM-rand	(6.81e-16,0.190)	(5.43e-16,0.0348)	(5.26e-16,0.0386)

(n, d, s, σ)	(100,10,0)	(200,10,0)	(300,10,0)
Fixed	(2.79e-15,0.255)	(1.22e-15,0.0532)	(1.10e-15,0.0196)
Reduced	(1.218e-15,0.0138)	(1.13e-15,1.26e-15)	(1.12e-15,1.43e-15)
EM-init	(1.026e-15,0.0453)	(8.93e-16,0.0126)	(9.61e-16,1.09e-15)
EM-rand	(1.32e-15,0.234)	(9.06e-16,0.0555)	(9.74e-16,0.0299)

(median,mean) over 100 trials(MLR) - Full Correct

Simulation Results - Low-dimensional case

$$y_i = x_i^T \beta_{z_i} + e_i, e_i \sim \mathcal{N}(0, \sigma^2)$$

(n, d, σ)	(1000,100,0)	(500,100,0)	(2000,100,0)
Fixed	(0.7326,0.7225)	(0.7975,0.7929)	(3.977e-12,0.2660)
Reduced	(6.9652e-12,0.006843)	(0.6181,0.4955)	(3.568e-12,3.644e-12)
EM-init	(2.0896e-12,0.006398)	(0.6010,0.5323)	(1.810e-12,1.7538e-12)
EM-rand	(0.8138,0.6981)	(1.044,1.0391)	(1.998e-12,0.1267)

(median,mean) over 100 trials(MLR) - Grad Descent(noiseless)

(n, d, σ)	(1000,100,0.05)	(1000,100,0.1)	(1000,100,0.3)
Fixed	(0.7482,0.7141)	(0.7357,0.7140)	(0.7687,0.7720)
Reduced	(0.03332,0.03346)	(0.07626,0.07683)	(0.3488,0.4067)
EM-init	(0.02516,0.02520)	(0.05192,0.05894)	(0.1986,0.2239)
EM-rand	(0.8242,0.6745)	(0.8156,0.7188)	(0.8694,0.8076)

(median,mean) over 100 trials(MLR) - Grad Descent(noisy)

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Simulation Results - High-dimensional case

(n, d, s, σ)	(200,1000,5,0)	(200,2000,5,0)	(200,2000,10,0)
Fixed	(0.6309,0.5142)	(0.5656,0.4758)	(0.8294,0.7917)
Reduced	(2.606e-12,0.2329)	(1.9967e-12,0.1903)	(0.7854,0.6780)
EM-rand	(0.7059,0.6198)	(0.8598,0.7714)	(0.9547,0.9660)

(median,mean) over 100 trials(MLR) - noiseless case

(n, d, s, σ)	(200,1000,5,0.05)	(200,1000,5,0.1)	(200,1000,5,0.3)
Fixed	(0.5302,0.4897)	(0.6341,0.5486)	(0.6648,0.6391)
Reduced	(0.02214,0.2270)	(0.05273,0.2802)	(0.3885,0.4501)
EM-rand	(0.6560,0.5450)	(0.7205,0.5980)	(0.7945,0.7487)

(median,mean) over 100 trials(MLR) - noisy case

Simulation Results - High-dimensional case

(n, d, s, σ)	(500,5000,10,0)	(1000,5000,20,0)
Fixed	(0.4928, 0.4285)	(0.7590,0.5964)
Reduced	(2.536e-13,0.02019)	(1.003e-13,0.02243)
EM-rand	(0.6856, 0.5507)	(0.3469,0.5763)

(median,mean) over 100 trials(MLR) - noiseless case

(n, d, s, σ)	(500,5000,10,0.05)	(500,5000,10,0.1)	(500,5000,10,0.3)
Fixed	(0.5699,0.4531)	(0.6228,0.5427)	(0.7077,0.6685)
Reduced	(0.01544,0.09110)	(0.03920,0.1083)	(0.3301,0.4112)
EM-rand	(0.8323,0.6422)	(0.7902,0.6005)	(0.9053,0.7963)

(median,mean) over 100 trials(MLR) - noisy case



Bhatia, Kush and Jain, Prateek and Kar, Purushottam(2015)

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