

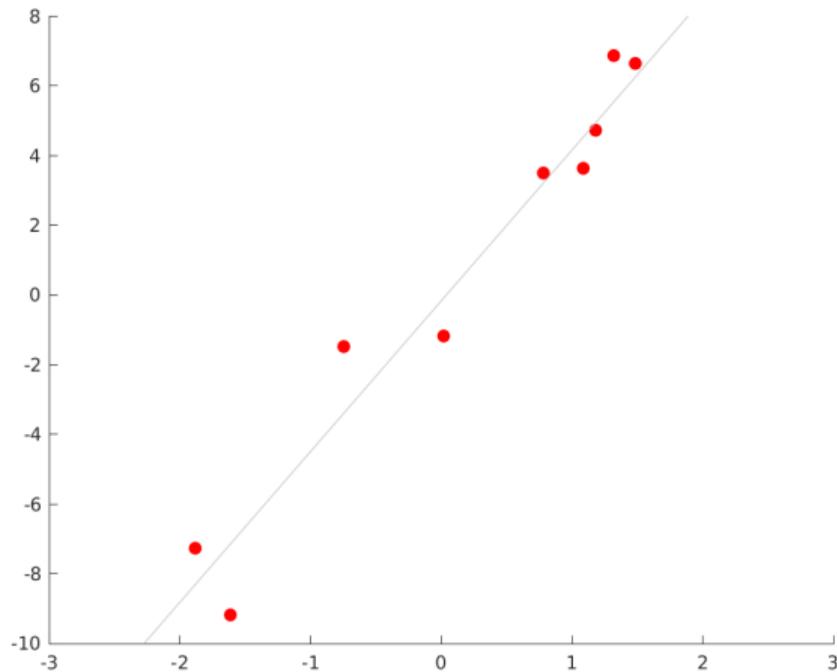
# **Sparse Mixed Linear Regression with Guarantees: Taming an Intractable Problem with Invex Relaxation**

**ICML 2022**

Adarsh Barik, Dr. Jean Honorio

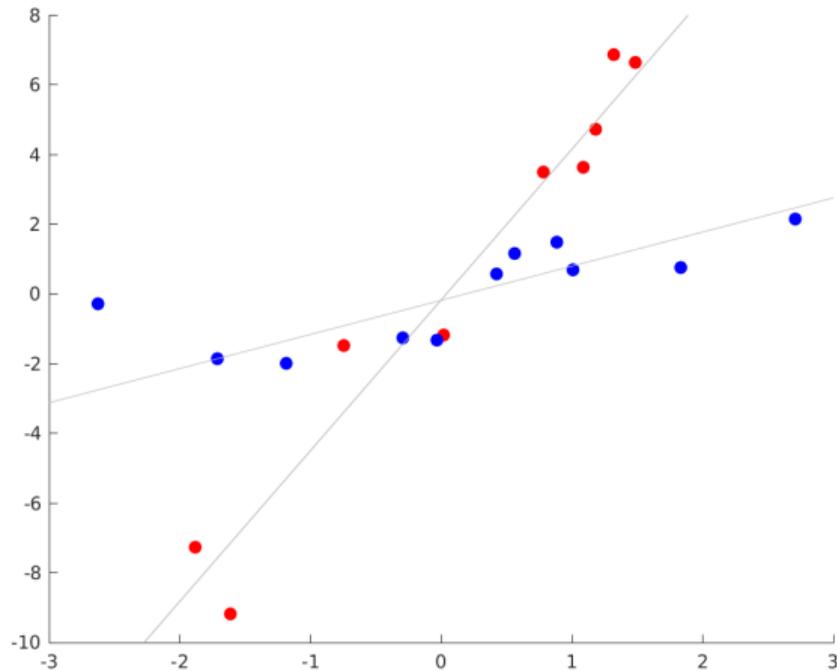
Purdue University

# Mixed Linear Regression (MLR)



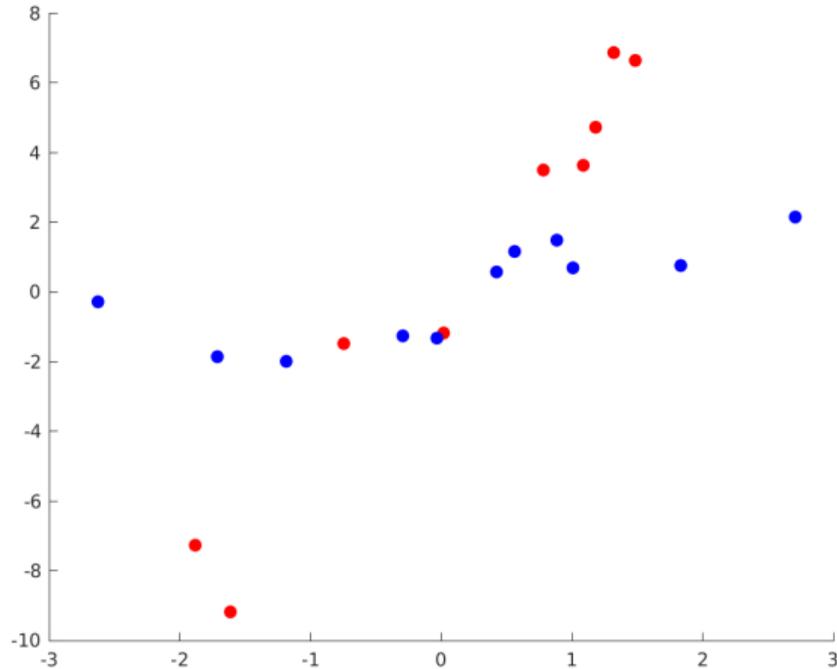
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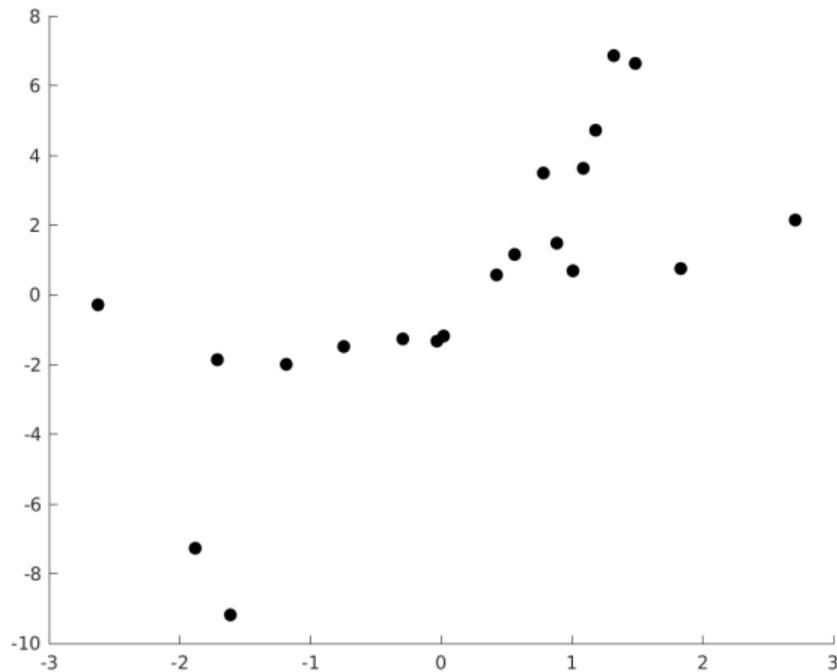
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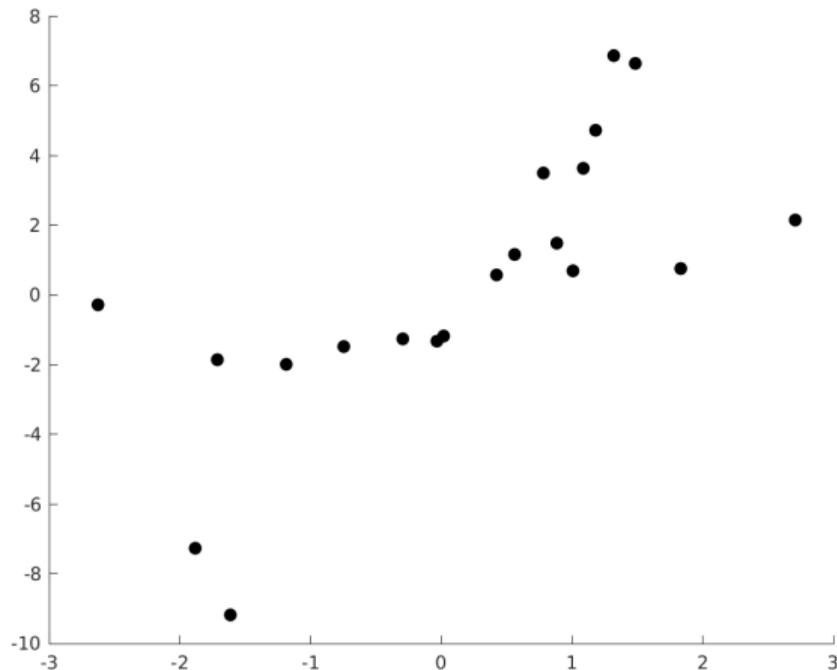
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## Mixed Linear Regression (MLR)



- $y_i = z_i^* \langle X_i, \beta_1^* \rangle + (1 - z_i^*) \langle X_i, \beta_2^* \rangle + e_i$
- Recover  $\beta_1^*$ ,  $\beta_2^*$  and  $z_i^*$  from data  $(X_i, y_i), \forall i \in \{1, \dots, n\}$

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- Applications: Music perception studies [Viele & Tong, 2002], Vehicle merging [Li et al., 2019]

## Combinatorial Formulation

- Given attributes  $X \in \mathbb{R}^{n \times d}$  and response  $y \in \mathbb{R}^n$
- Recover **sparse** parameters  $\beta_1 \in \mathbb{R}^d$  and  $\beta_2 \in \mathbb{R}^d$
- Recover **hidden** labels  $z \in \{0, 1\}^n$
- **Combinatorial** MLR

$$\begin{aligned} \min_{\beta_1, \beta_2, z} & \frac{1}{n} \left( \sum_{i=1}^n z_i (y_i - \langle X_i, \beta_1 \rangle)^2 + (1 - z_i) (y_i - \langle X_i, \beta_2 \rangle)^2 \right) \\ \text{subject to} & \quad z_i \in \{0, 1\}, \quad \forall i \in \{1, \dots, n\} \\ & \quad \|\beta_1\|_0 = s_1, \quad \|\beta_2\|_0 = s_2 \end{aligned}$$

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**Non-convex** even after continuous relaxation and regularization!

## Invex Relaxation

- Given attributes  $X \in \mathbb{R}^{n \times d}$  and response  $y \in \mathbb{R}^n$  and  $S_i = \begin{bmatrix} X_i \\ -y_i \end{bmatrix} \begin{bmatrix} X_i^T & -y_i \end{bmatrix}$
- Recover **sparse** matrices  $W \in \mathbb{R}^{d+1 \times d+1}$ ,  $U \in \mathbb{R}^{d+1 \times d+1}$  and **hidden** labels  $t \in \{-1, +1\}^n$
- Invex** MLR

$$\begin{aligned} \min_{t, W, U} & \frac{1}{2} (\sum_{i=1}^n \langle S_i, W + U \rangle + t_i \langle S_i, W - U \rangle) + \lambda_1 \|W(\cdot)\|_1 + \lambda_2 \|U(\cdot)\|_1 \\ \text{subject to} & \quad W \succeq \mathbf{0}, \quad U \succeq \mathbf{0} \\ & \quad W_{d+1, d+1} = 1, \quad U_{d+1, d+1} = 1 \\ & \quad \|t\|_\infty \leq 1 \end{aligned}$$

**Intuition:**  $\begin{bmatrix} \beta_1 \\ 1 \end{bmatrix} \begin{bmatrix} \beta_1^T & 1 \end{bmatrix} \succeq \mathbf{0}, \begin{bmatrix} \beta_2 \\ 1 \end{bmatrix} \begin{bmatrix} \beta_2^T & 1 \end{bmatrix} \succeq \mathbf{0}, z_i = \frac{t_i + 1}{2}$

# Invexity

- A function  $\phi$  is  $\eta$ -invex iff

$$\phi(\mathbf{u}) - \phi(\mathbf{v}) \geq \nabla\phi(\mathbf{v})^T \eta(\mathbf{u}, \mathbf{v}) \quad \forall \mathbf{u}, \mathbf{v}$$

- A convex function  $\phi$  is  $\eta$ -invex for  $\eta(\mathbf{u}, \mathbf{v}) = \mathbf{u} - \mathbf{v}$ .
- KKT conditions
  - **necessary** even for non-convex problems
  - **sufficient** for invex problems [Hanson, 1981]
  - Come up with unique primal and dual variables which satisfy KKT conditions

## Invex Formulation

- **Invex** MLR

$$\begin{aligned} \min_{\mathbf{t}, \mathbf{W}, \mathbf{u}} \quad & \frac{1}{2} (\sum_{i=1}^n \langle \mathbf{S}_i, \mathbf{W} + \mathbf{u} \rangle + t_i \langle \mathbf{S}_i, \mathbf{W} - \mathbf{u} \rangle) + \lambda_1 \|\mathbf{W}(\cdot)\|_1 + \lambda_2 \|\mathbf{u}(\cdot)\|_1 \\ \text{subject to} \quad & \mathbf{W} \succeq \mathbf{0}, \quad \mathbf{u} \succeq \mathbf{0} \\ & \mathbf{W}_{d+1,d+1} = 1, \quad \mathbf{u}_{d+1,d+1} = 1 \\ & \|\mathbf{t}\|_\infty \leq 1 \end{aligned}$$

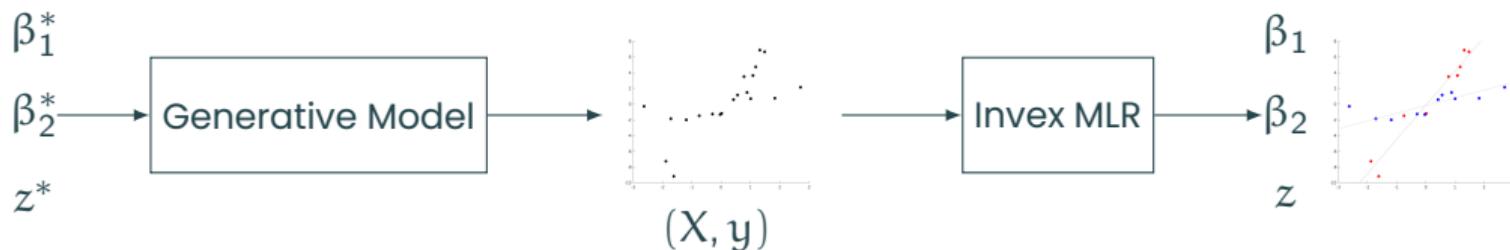
- Functions are  $\eta$ -invex for

$$\eta((\mathbf{t}, \mathbf{W}, \mathbf{u}), (\tilde{\mathbf{t}}, \tilde{\mathbf{W}}, \tilde{\mathbf{u}})) = \begin{bmatrix} \mathbf{0} \\ -\tilde{\mathbf{W}} \\ -\tilde{\mathbf{u}} \end{bmatrix}$$

# Generative Model

- **True** sparse parameters and hidden labels:  $\beta_1^* \in \mathbb{R}^d$ ,  $\beta_2^* \in \mathbb{R}^d$ ,  $z^* \in \{0, 1\}^n$
- Random attributes and independent noise:  $X \in \mathbb{R}^{n \times d}$ ,  $e \in \mathbb{R}^n$
- The response  $y_i \in \mathbb{R}$  is generated by:

$$y_i = z_i^* \langle X_i, \beta_1^* \rangle + (1 - z_i^*) \langle X_i, \beta_2^* \rangle + e_i \quad \forall i \in \{1, \dots, n\}$$



## Exact Recovery Guarantee

- Let  $S(\beta) = \{i | \beta_i \neq 0\}$  be the support of  $\beta \in \mathbb{R}^d$
- $\sum_{i=1}^n z_i^* = n_1, \quad n_2 = n - n_1$
- **Invex** MLR outputs the **true** solution

$$S(\beta_1) = S(\beta_1^*), \quad S(\beta_2) = S(\beta_2^*), \quad z = z^*$$

with high probability provided that:

$$n_1 \geq \Omega(|S(\beta_1^*)|^3 \log d), \quad n_2 \geq \Omega(|S(\beta_2^*)|^3 \log d)$$

- Furthermore,  $\|\beta_1 - \beta_1^*\|_2 \leq \delta, \quad \|\beta_2 - \beta_2^*\|_2 \leq \delta.$

**Thank You!**