

MODEL FITTING II

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9/21/2017

RECAP

- * Linear regression, L2 loss (minimizing squared error)

RECAP

- * Regularization
- * Prior
- * Penalty
- * Geometry / ad hoc (early stopping)

RECAP

- * Families of regularized models
 - * L2 / ridge / grad. descent w/ early stopping
 - * L1 / LASSO / coord. descent w/ early stopping
 - * L0 / feature selection

1D EXAMPLE

subject



stimulus



- * y = output of a neuron that you are measuring
- * x = how many times per second the screen flashes

1D EXAMPLE

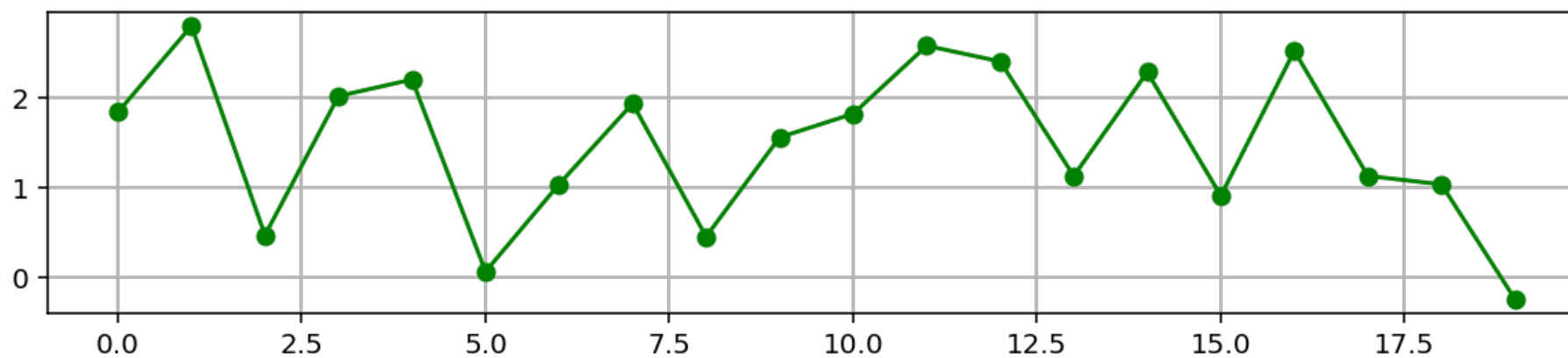
subject



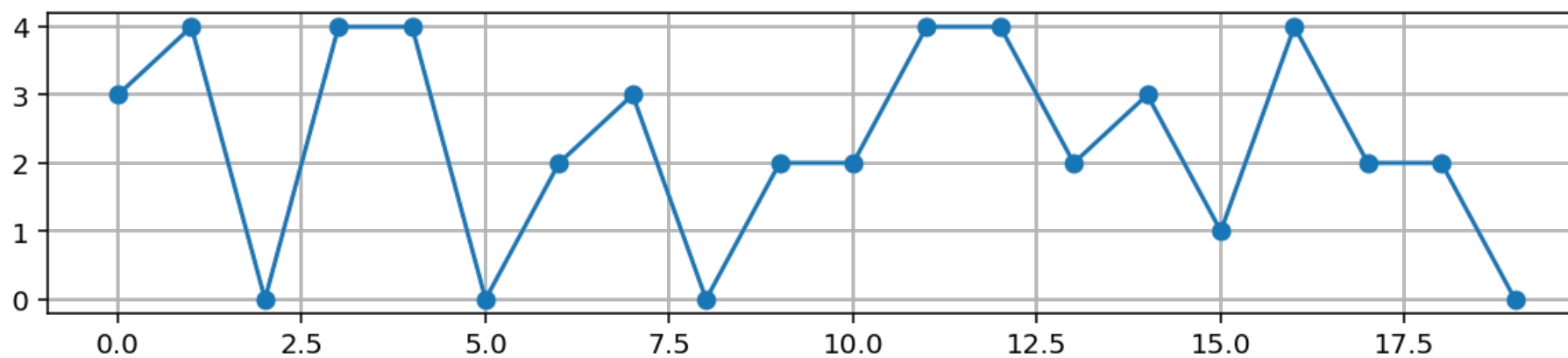
stimulus



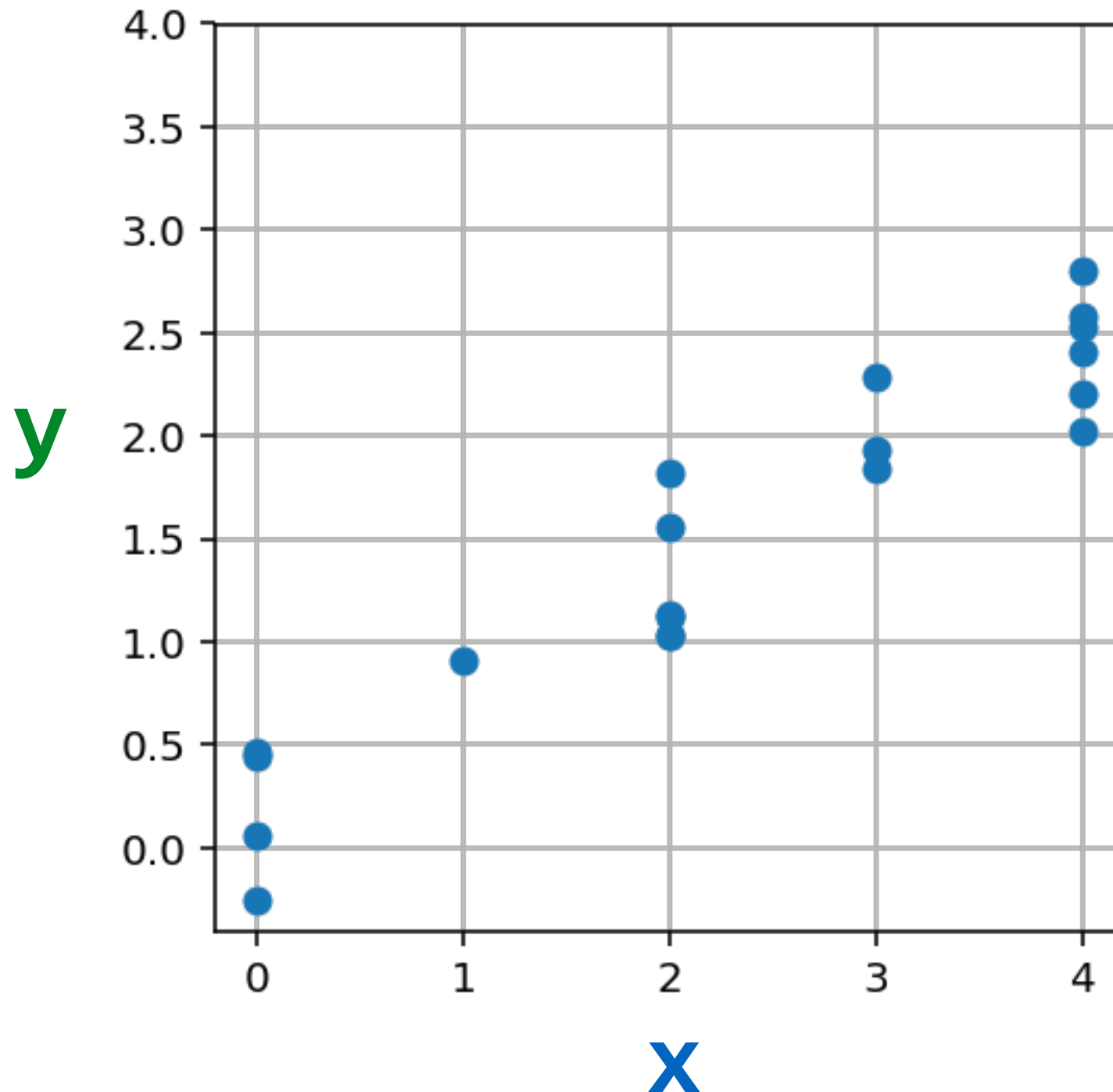
y



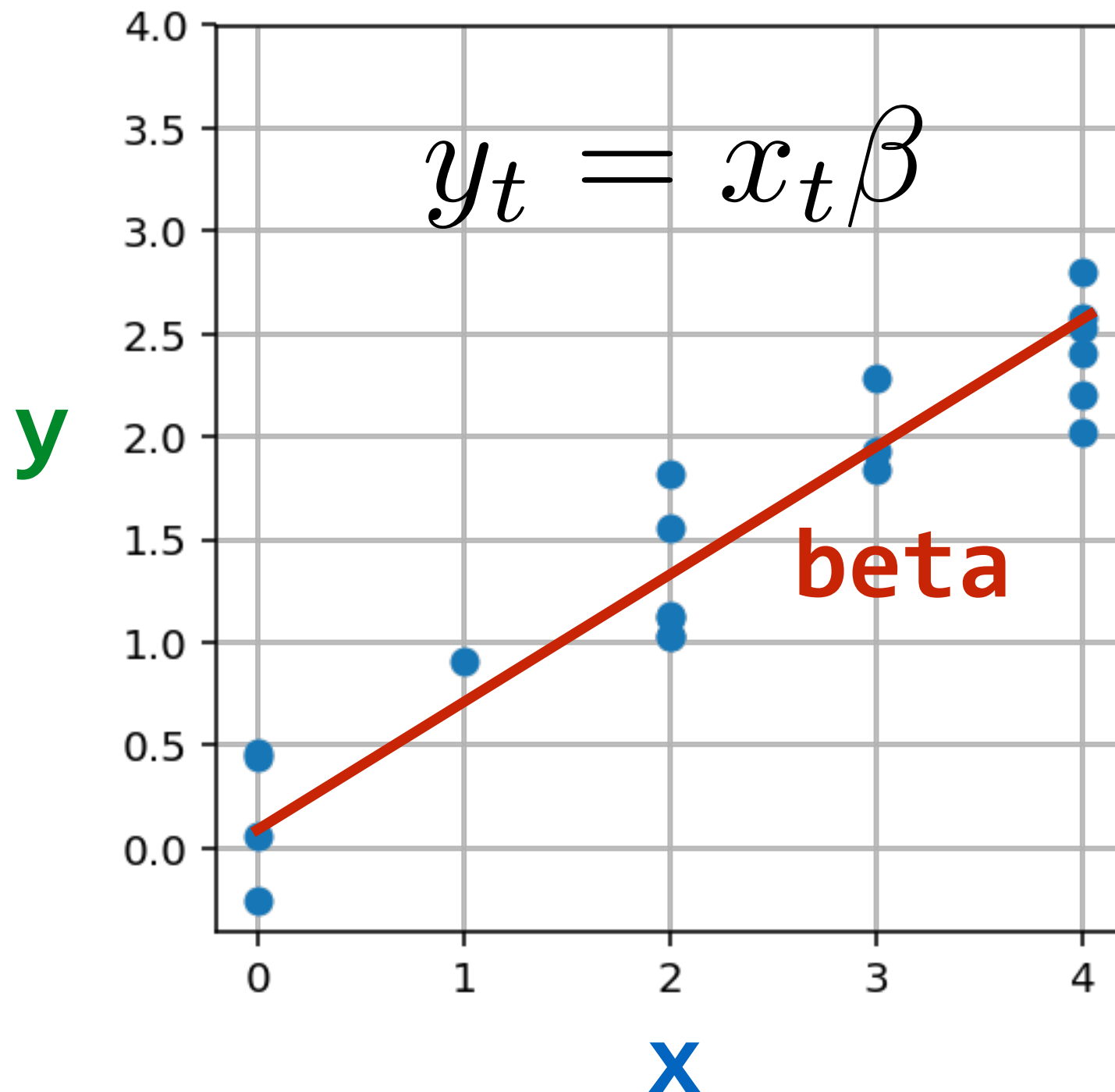
x



1D EXAMPLE



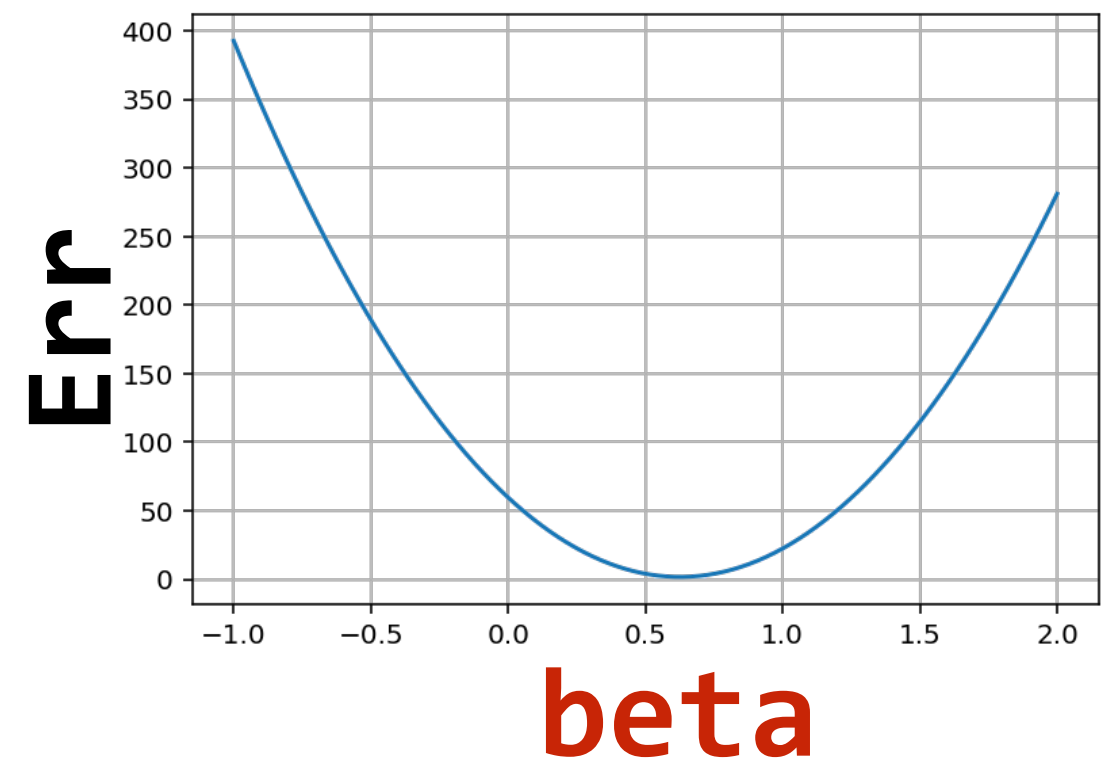
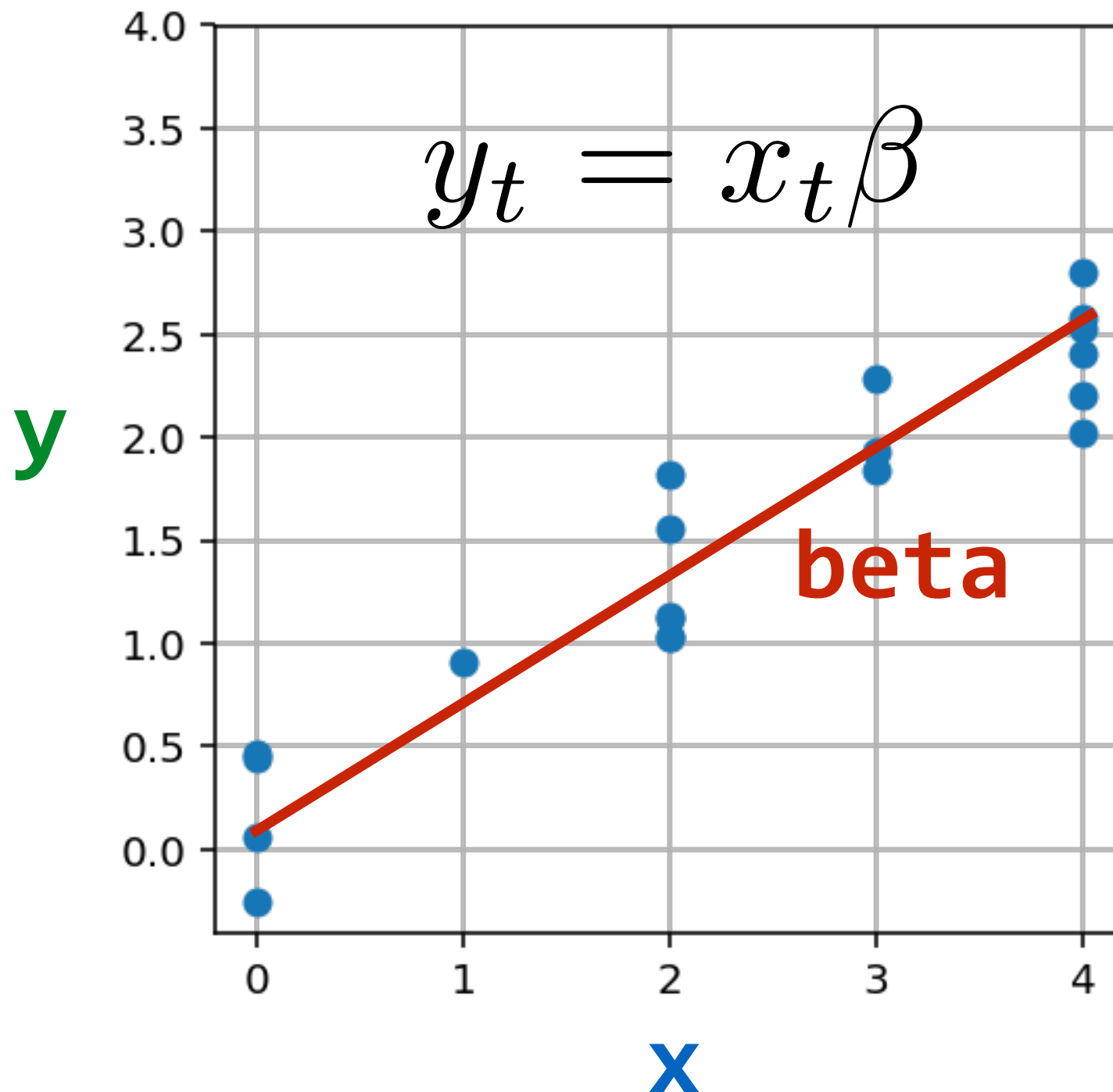
1D EXAMPLE



1D EXAMPLE

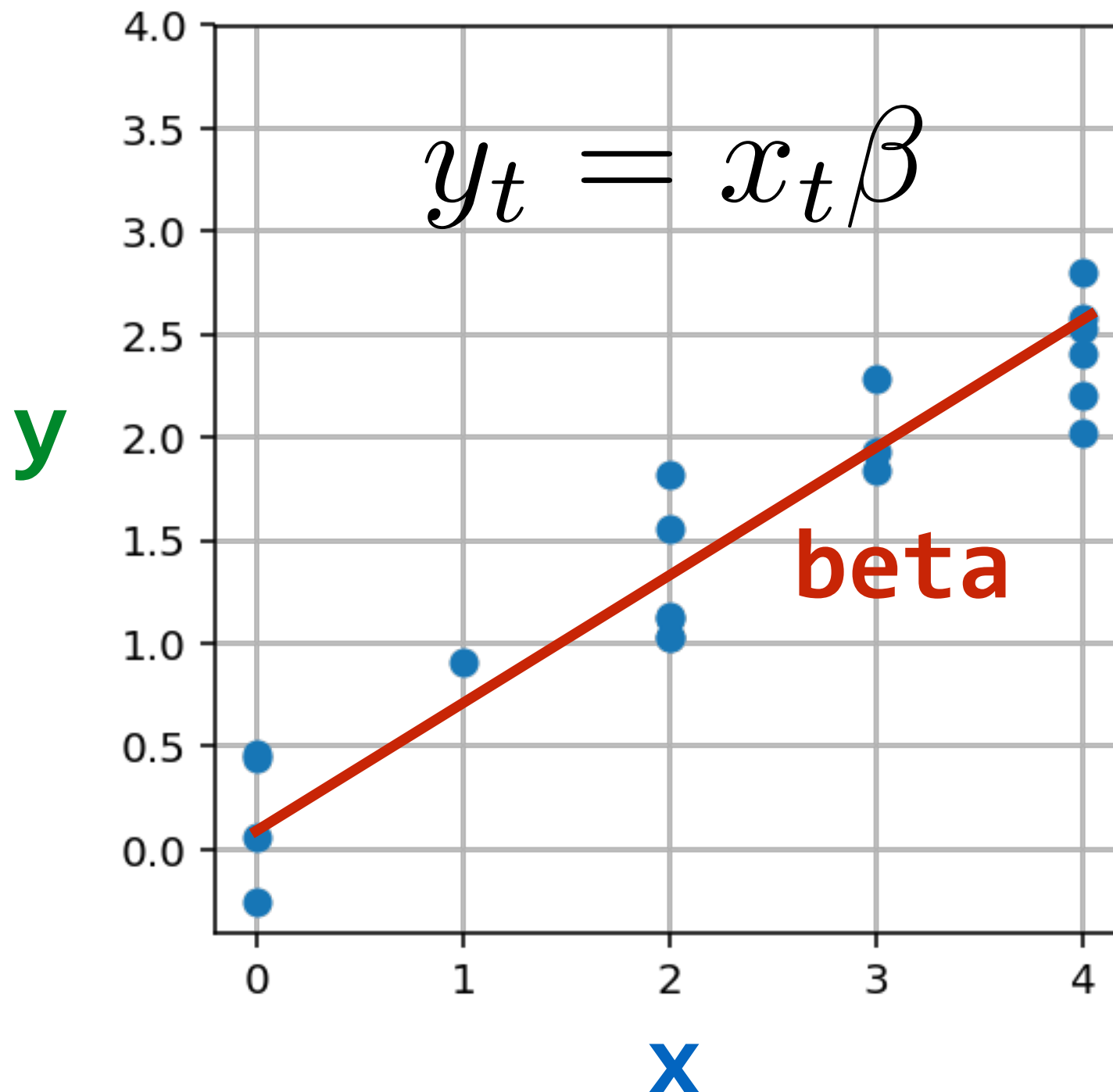
$$\text{Err}(\beta) = \sum_{t=1}^T (y_t - x_t \beta)^2$$

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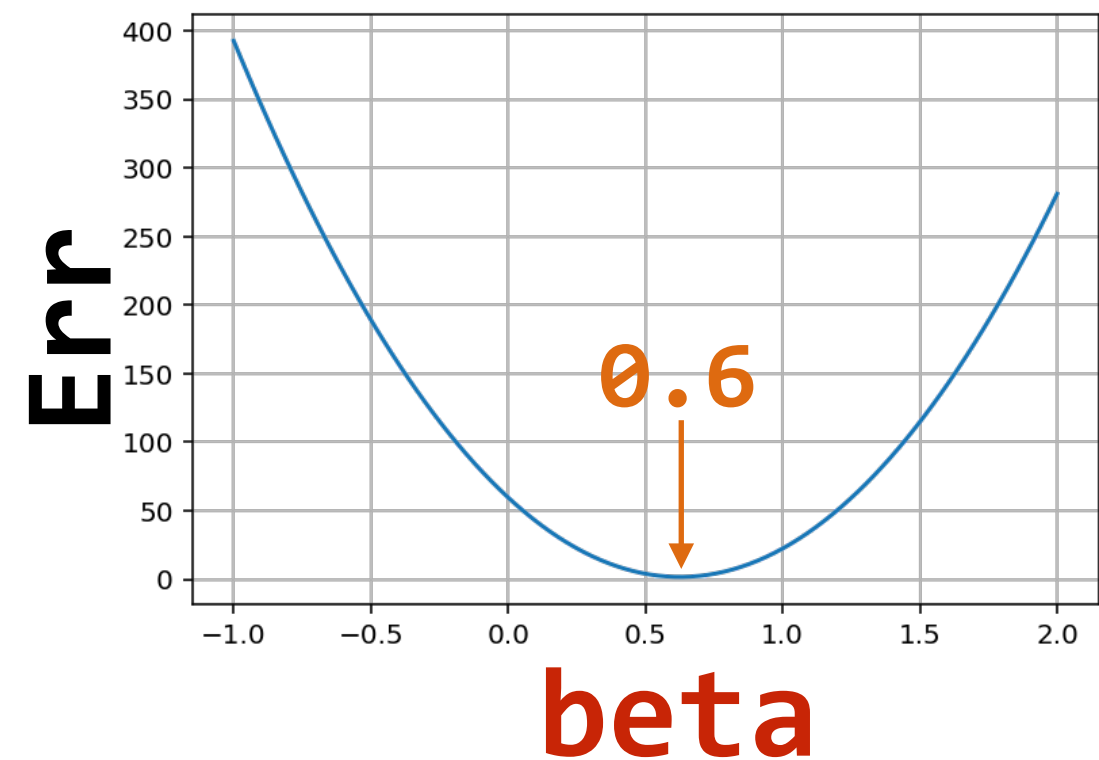


1D EXAMPLE

$$\text{Err}(\beta) = \sum_{t=1}^T (y_t - x_t \beta)^2$$

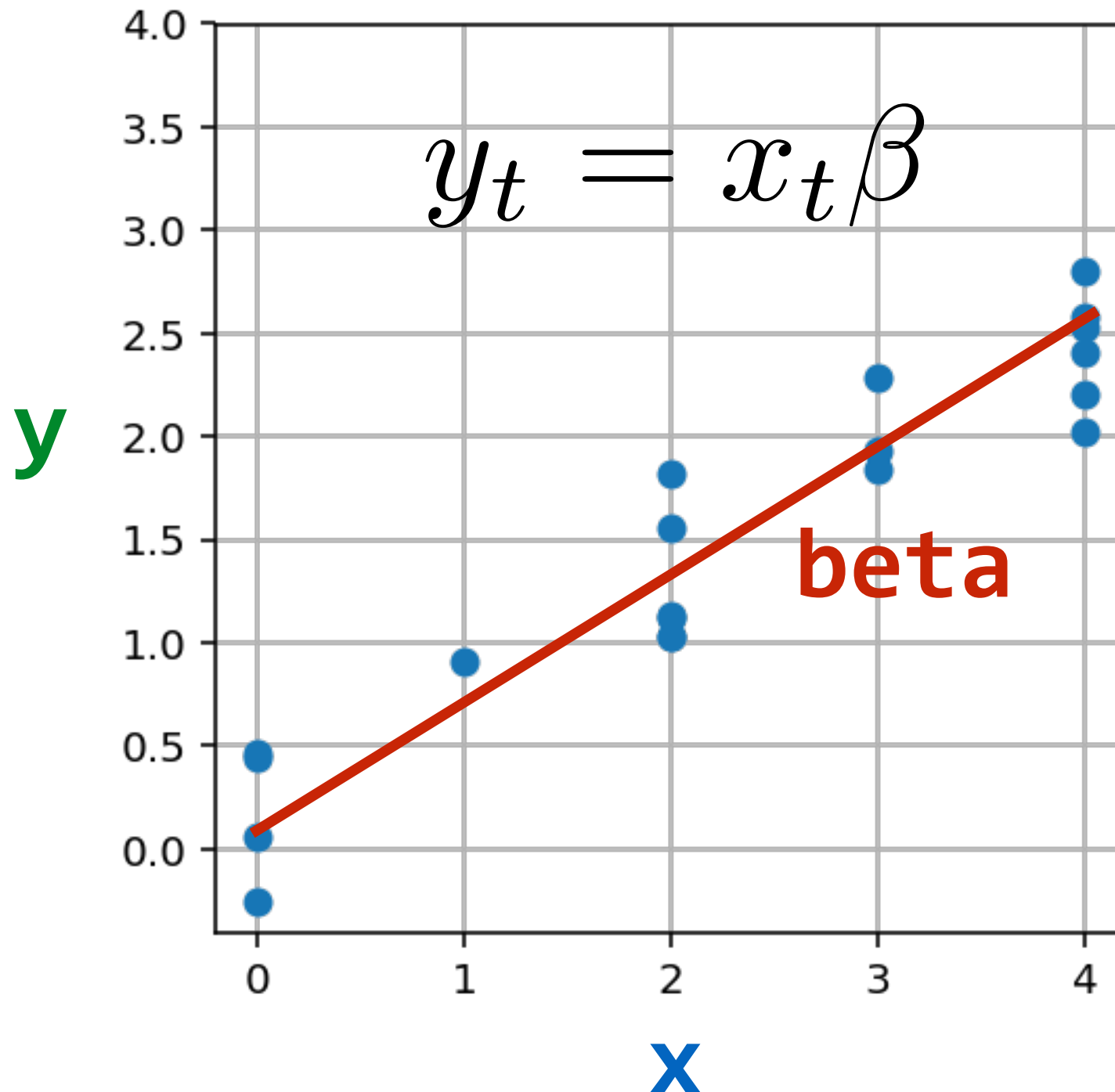


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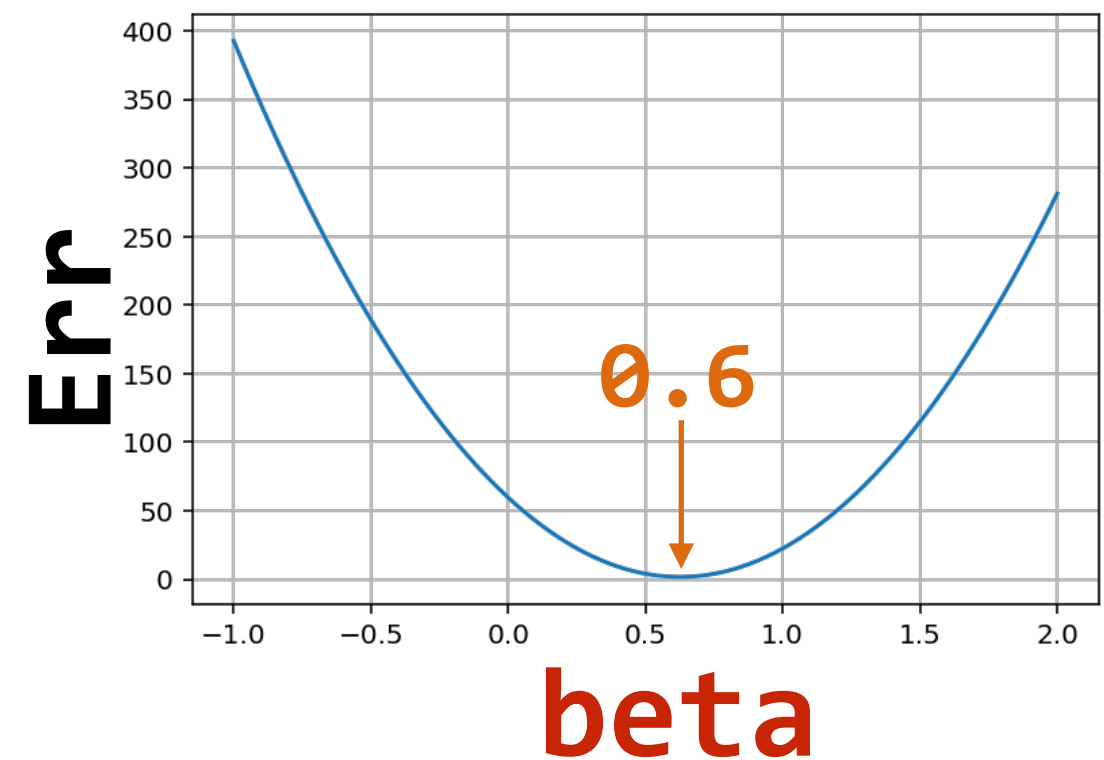


1D EXAMPLE

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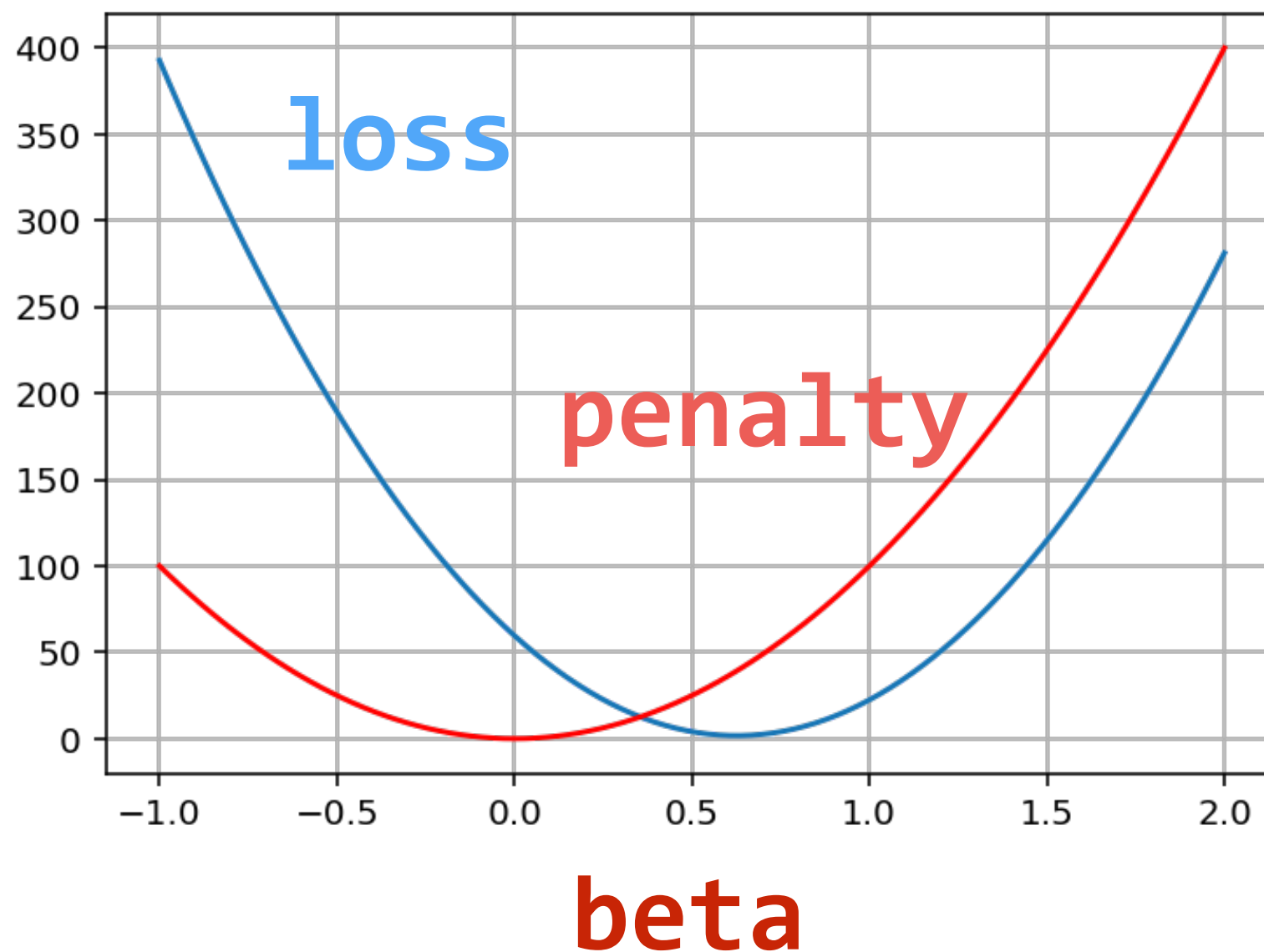


$$Err(\beta) = \sum_{t=1}^T (y_t - x_t \beta)^2 + \lambda \beta^2$$

1D EXAMPLE

L2 Regularization:
(as penalty)

$$Err(\beta) = \sum_{t=1}^T (y_t - x_t \beta)^2 + \lambda \beta^2$$

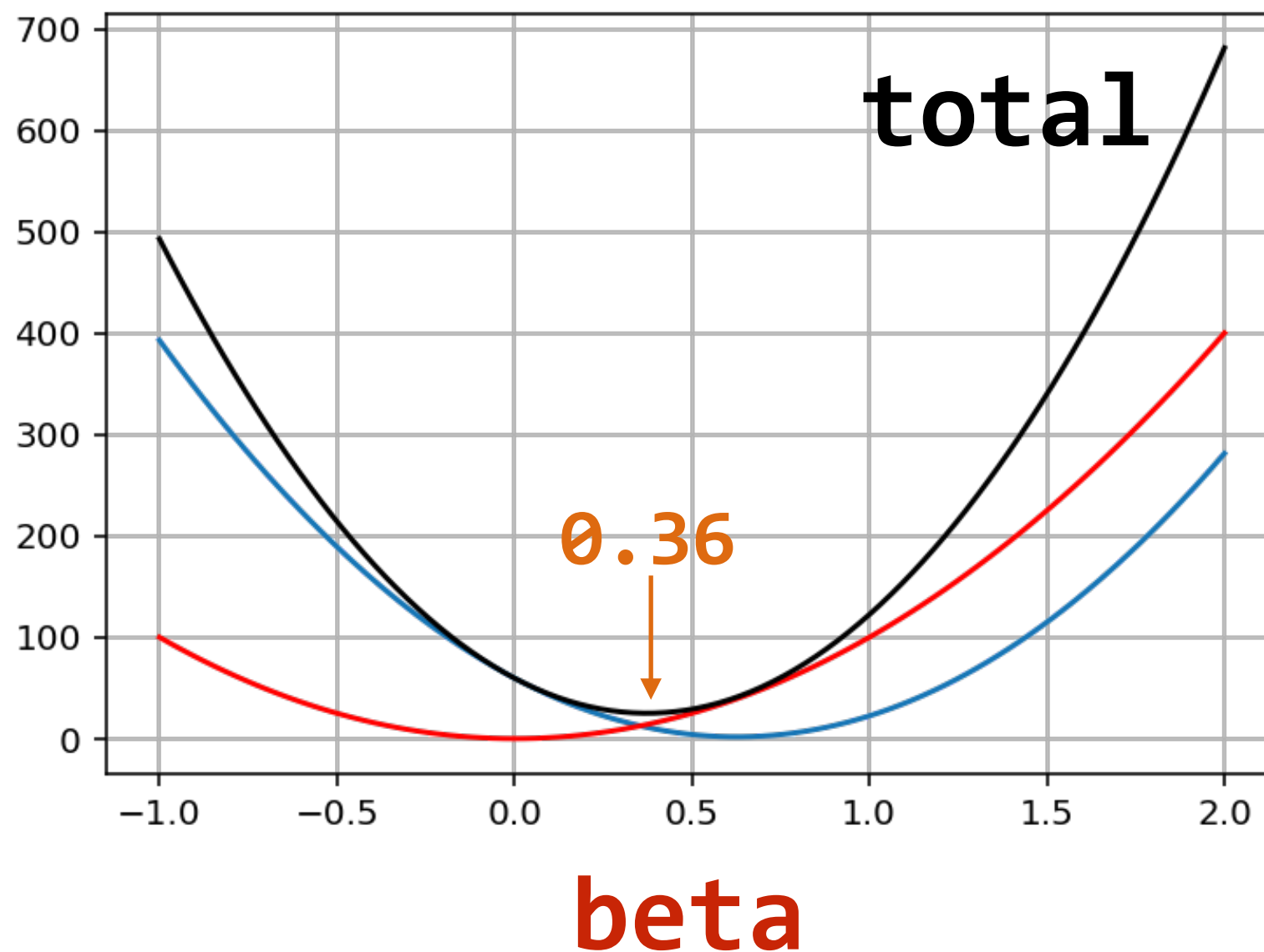


$$Err(\beta) = \sum_{t=1}^T (y_t - x_t \beta)^2 + \lambda \beta^2$$

1D EXAMPLE

L2 Regularization:
(as penalty)

$$Err(\beta) = \sum_{t=1}^T (y_t - x_t \beta)^2 + \lambda \beta^2$$



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1D EXAMPLE

L1 Regularization:
(as penalty)

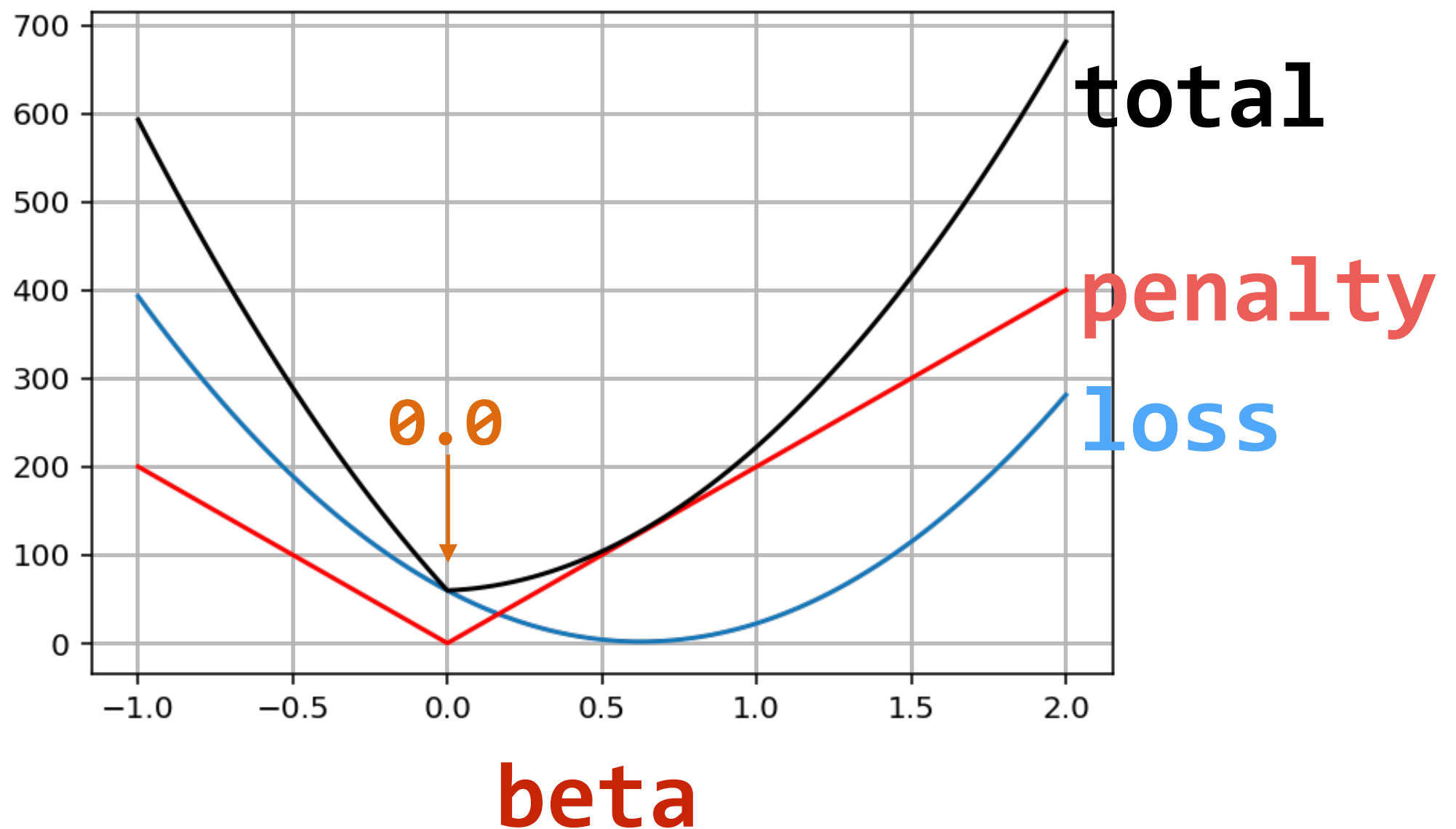
$$\text{Err}(\beta) = \sum_{t=1}^T (y_t - x_t \beta)^2 + \lambda |\beta|$$

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1D EXAMPLE

L1 Regularization:
(as penalty)

$$Err(\beta) = \sum_{t=1}^T (y_t - x_t \beta)^2 + \lambda |\beta|$$

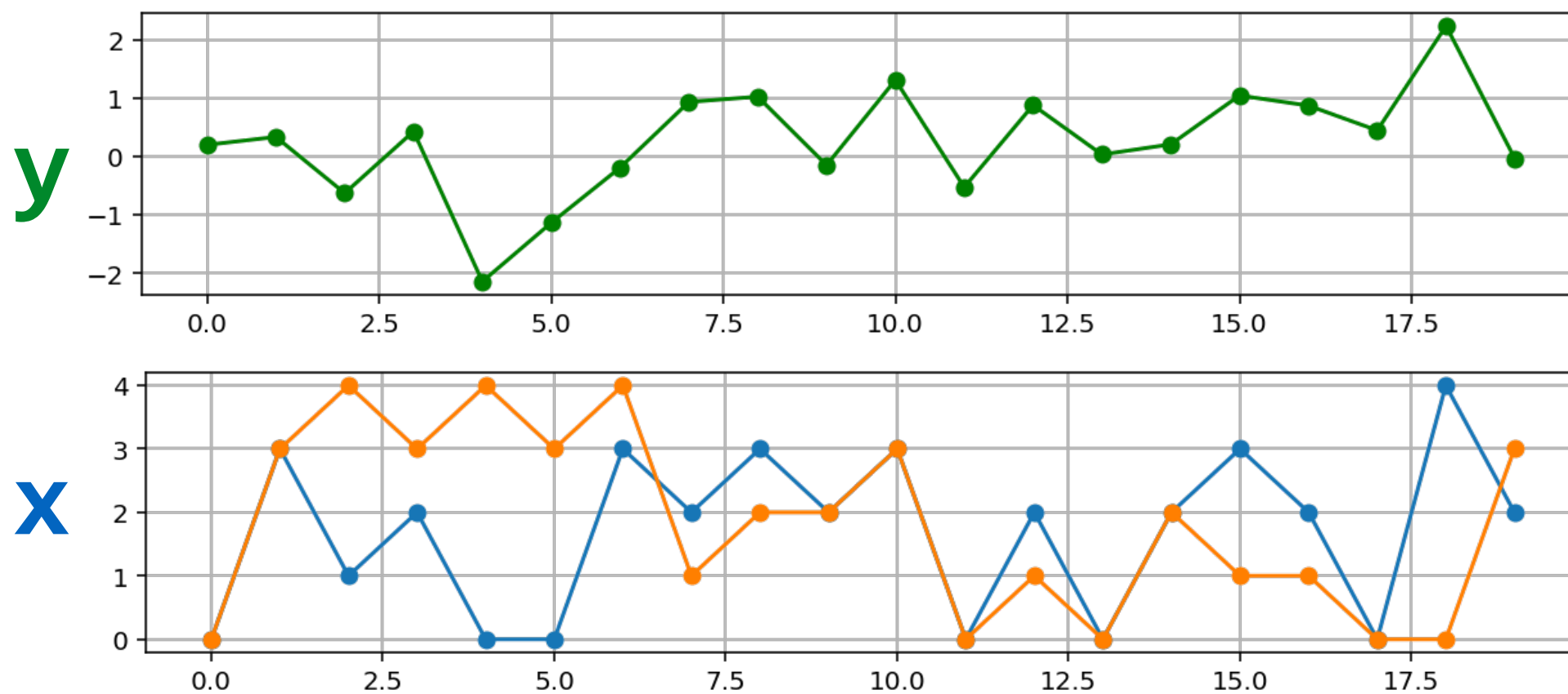


2D EXAMPLE

subject

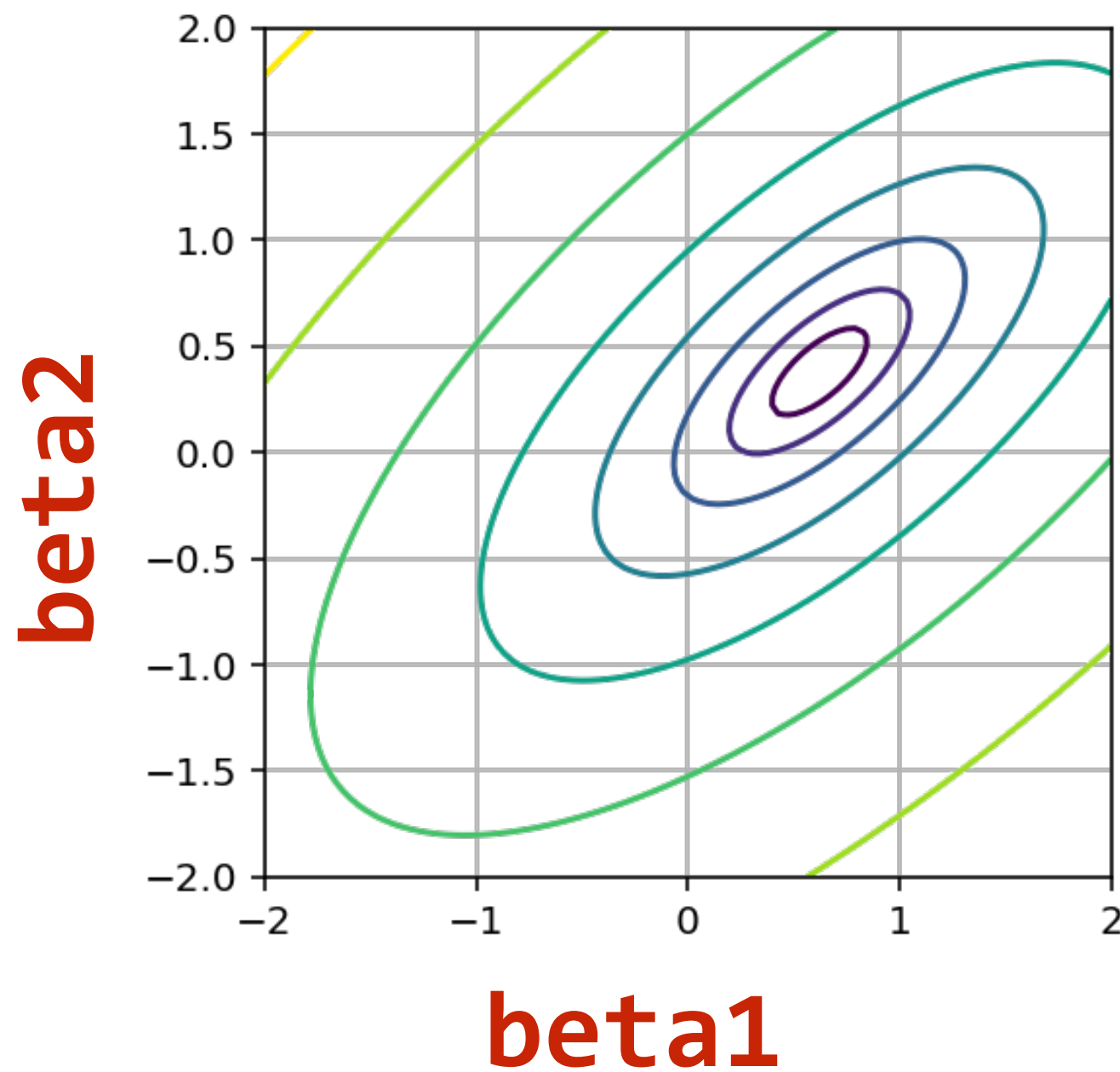


stimulus



2D EXAMPLE

$$y_t = x_{1,t}\beta_1 + x_{2,t}\beta_2$$



LASSO

- * Laplacian prior on β_i
- * L1 penalty on β
- * Coordinate descent w/ early stopping

LASSO

$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \left[\|Y - X\beta\|_2^2 + \lambda \|\beta\|_1 \right]$

$\hat{\beta} = \underset{\beta}{\operatorname{argmin}}$

$$Y = X\beta + \epsilon$$

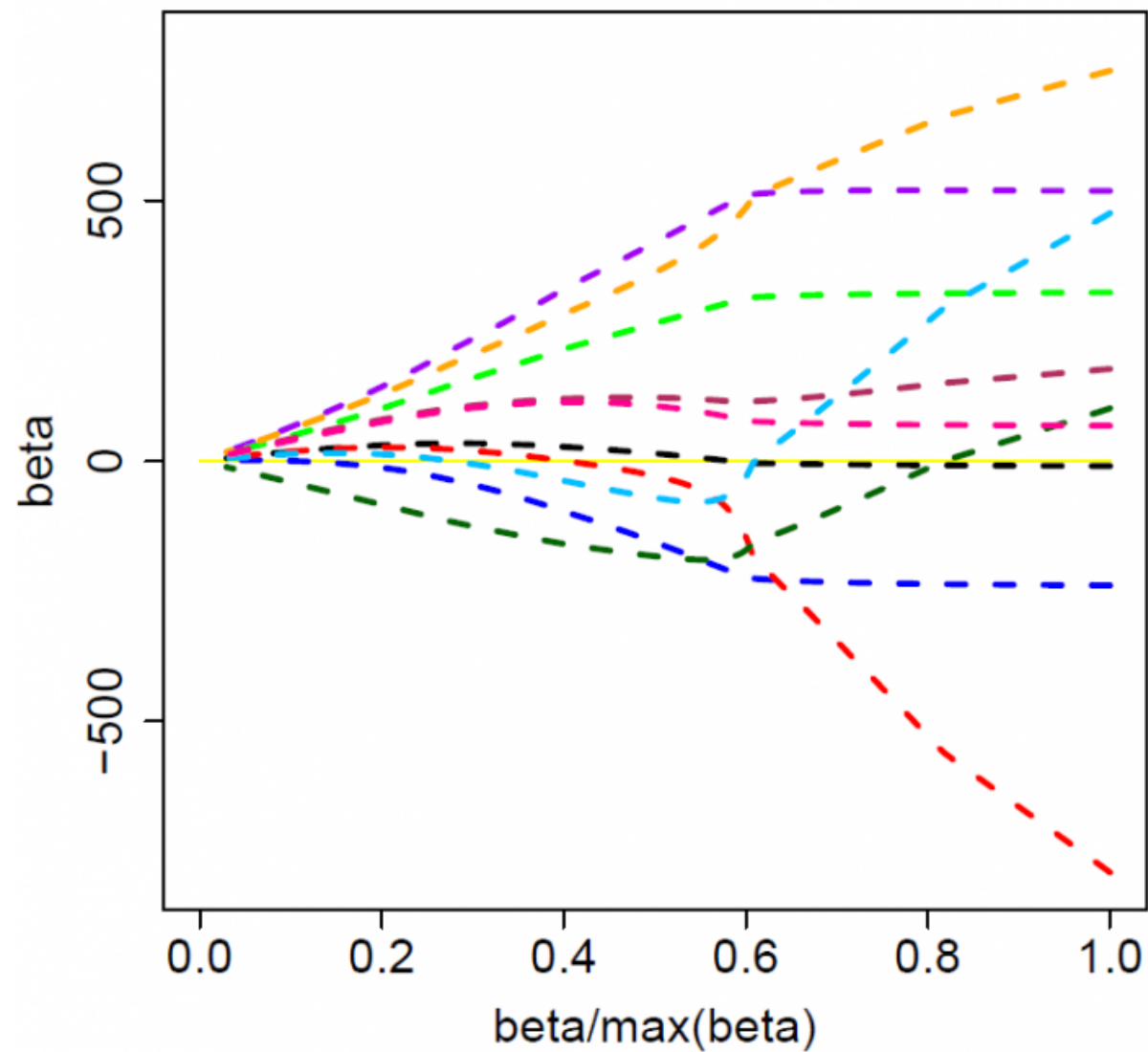
$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \left[\underbrace{\|Y - X\beta\|_2^2}_{\text{ERROR or LOSS}} + \underbrace{\lambda \|\beta\|_1}_{\text{PENALTY}} \right]$$

LASSO

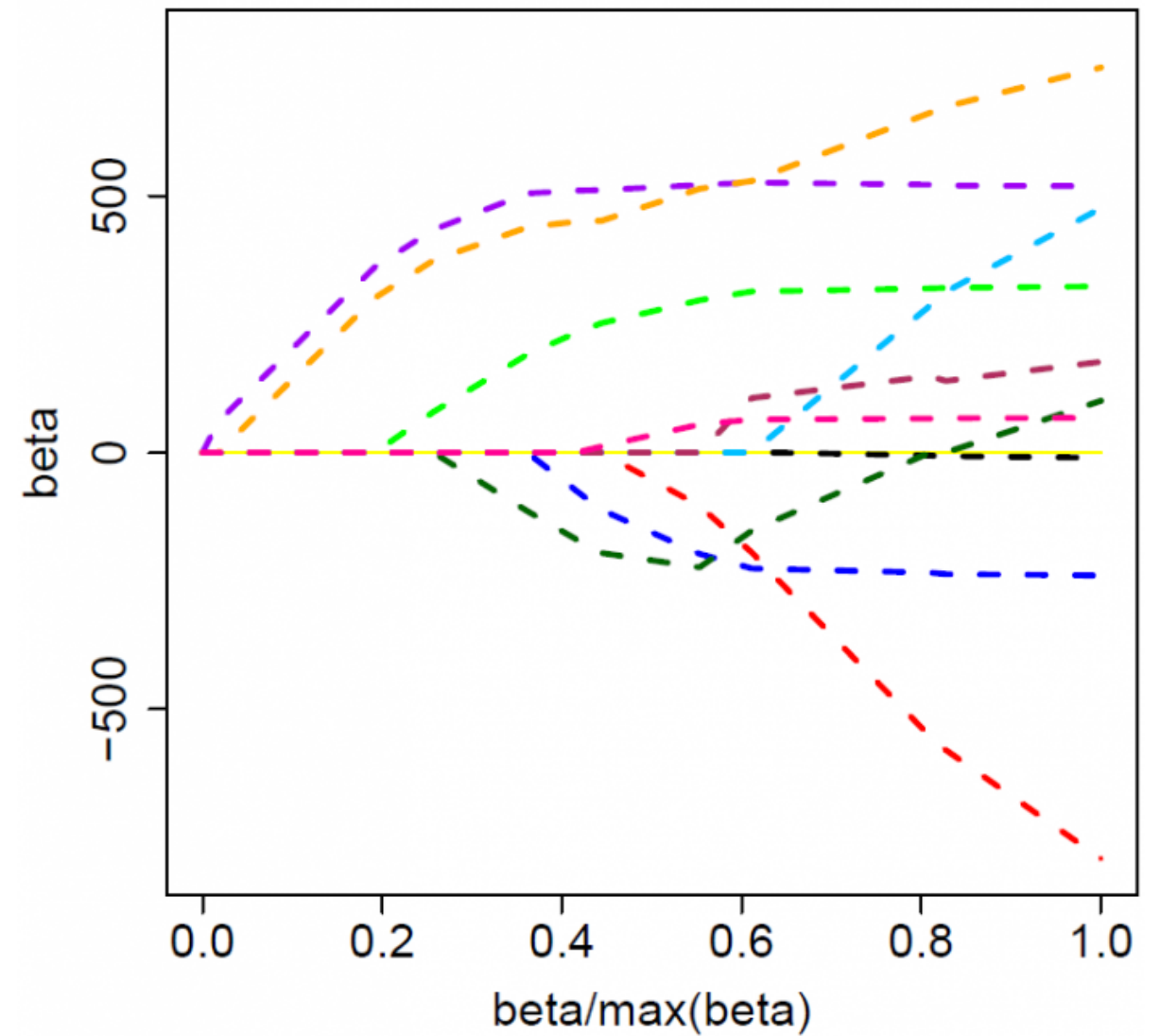
- * No closed form solution
- * Solved via coordinate descent, LARS (least-angle regression) or other methods
- * *SssssLLLLLoooooWWWW.....*

LASSO

Ridge Regression



Ordinary Lasso



OTHER METHODS

- * Neural networks
- * Random forests
- * Feature selection ($\sim L_0$ -norm)