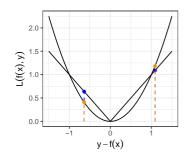
## **Introduction to Machine Learning**

# Supervised Regression Linear Models with *L*1 Loss



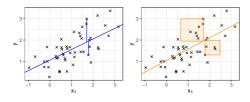


#### Learning goals

- Understand difference between L1 and L2 regression
- See how choice of loss affects optimization & robustness

#### **ABSOLUTE LOSS**

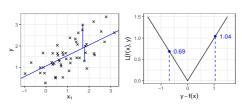
• L2 regression minimizes quadratic residuals – wouldn't **absolute** residuals seem more natural?



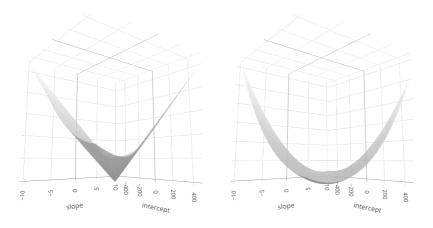


• L1 loss / absolute error / least absolute deviation (LAD)

$$L(y, f(\mathbf{x})) = |y - f(\mathbf{x})|$$



### L1 VS L2 - LOSS SURFACE





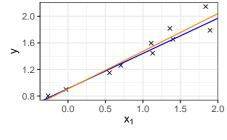
L1 loss (left) harder to optimize than L2 loss (right)

- Convex but **not differentiable** in  $y f(\mathbf{x}) = 0$
- No analytical solution

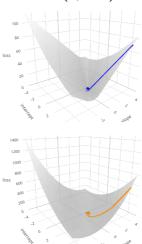
#### L1 VS L2 - ESTIMATED PARAMETERS

- Results of *L*1 and *L*2 regression often not that different
- Simulated data:  $y^{(i)} = 1 + 0.5x_1^{(i)} + \epsilon^{(i)}$ ,  $\epsilon^{(i)} \stackrel{i.i.d}{\sim} \mathcal{N}(0, 0.01)$

	intercept	slope
<i>L</i> 1	0.91	0.53
L2	0.91	0.57



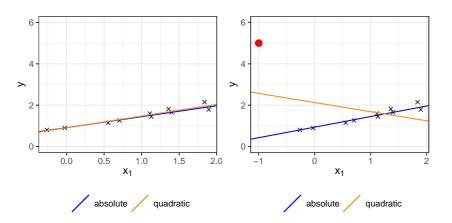






#### L1 VS L2 - ROBUSTNESS

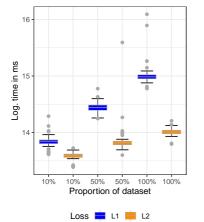
- L2 quadratic in residuals → outlying points carry lots of weight
- $\bullet \ \ \text{E.g., } 3 \times \text{residual} \Rightarrow 9 \times \text{loss contribution}$
- L1 more **robust** in presence of outliers (example ctd.):





#### L1 VS L2 - OPTIMIZATION COST

- Compare time to fit L1 (quantreg::rq()) vs L2 (lm::lm()) for different dataset proportions (repeat 50×)



Loss						
	Fitted: L1	Fitted: L2				
Total L1 loss	$8.98 \times 10^{4}$	$8.99 \times 10^{4}$				
Total L2 loss	$5.83 \times 10^{6}$	$5.81 \times 10^{6}$				

#### Estimated coefficients

$x_j$	L1: $\hat{ heta}_j$	L2: $\hat{\theta}_j$
Max_temperature	0.553	0.563
Min_temperature	0.441	0.427
Visibility	0.026	0.041
Wind_speed	0.002	0.010
Max_wind_speed	-0.026	-0.039
(Intercept)	-0.380	-0.102

L1 slower to optimize!

