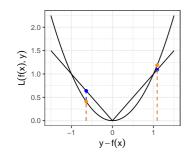
Introduction to Machine Learning

Supervised Regression: Linear Models with *L*1 Loss



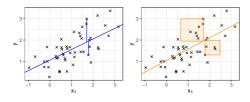
Learning goals

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



ABSOLUTE LOSS

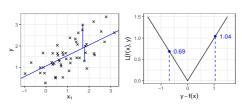
• L2 regression minimizes quadratic residuals – wouldn't **absolute** residuals seem more natural?



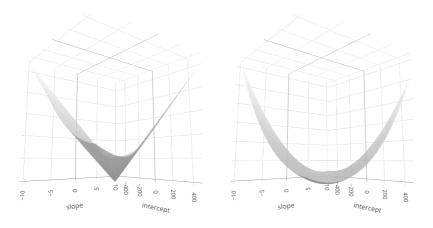


• L1 loss / absolute error / least absolute deviation (LAD)

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



L1 VS L2 - LOSS SURFACE





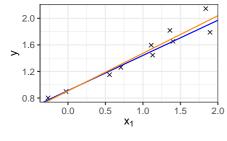
L1 loss (left) harder to optimize than L2 loss (right)

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

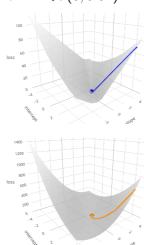
L1 VS L2 - ESTIMATED PARAMETERS

- Results of L1 and L2 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



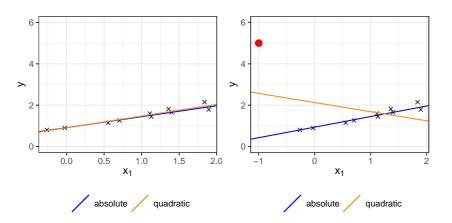






L1 VS L2 - ROBUSTNESS

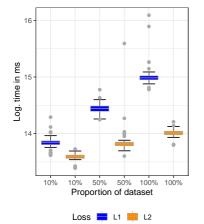
- L2 quadratic in residuals → outlying points carry lots of weight
- $\bullet \ \ \text{E.g., } 3 \times \text{residual} \Rightarrow 9 \times \text{loss contribution}$
- L1 more **robust** in presence of outliers (example ctd.):





L1 VS L2 - OPTIMIZATION COST

- Real-world weather problem → predict mean temperature
- 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	8.98×10^{4}	8.99×10^{4}				
Total L2 loss	5.83×10^{6}	5.81×10^{6}				

Estimated coefficients

x_j	L 1: $\hat{ heta}_j$	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!

