

Machine Learning and Data Mining

Loss Functions

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Loss functions

- Measure error in our predictions
 - A function of the parameters and training data
- $J(\theta) = \dots$
- Ideally, these should
 - Measure what we care about
 - Be easy to optimize over
- Often these two goals are in conflict...

Cost functions for regression

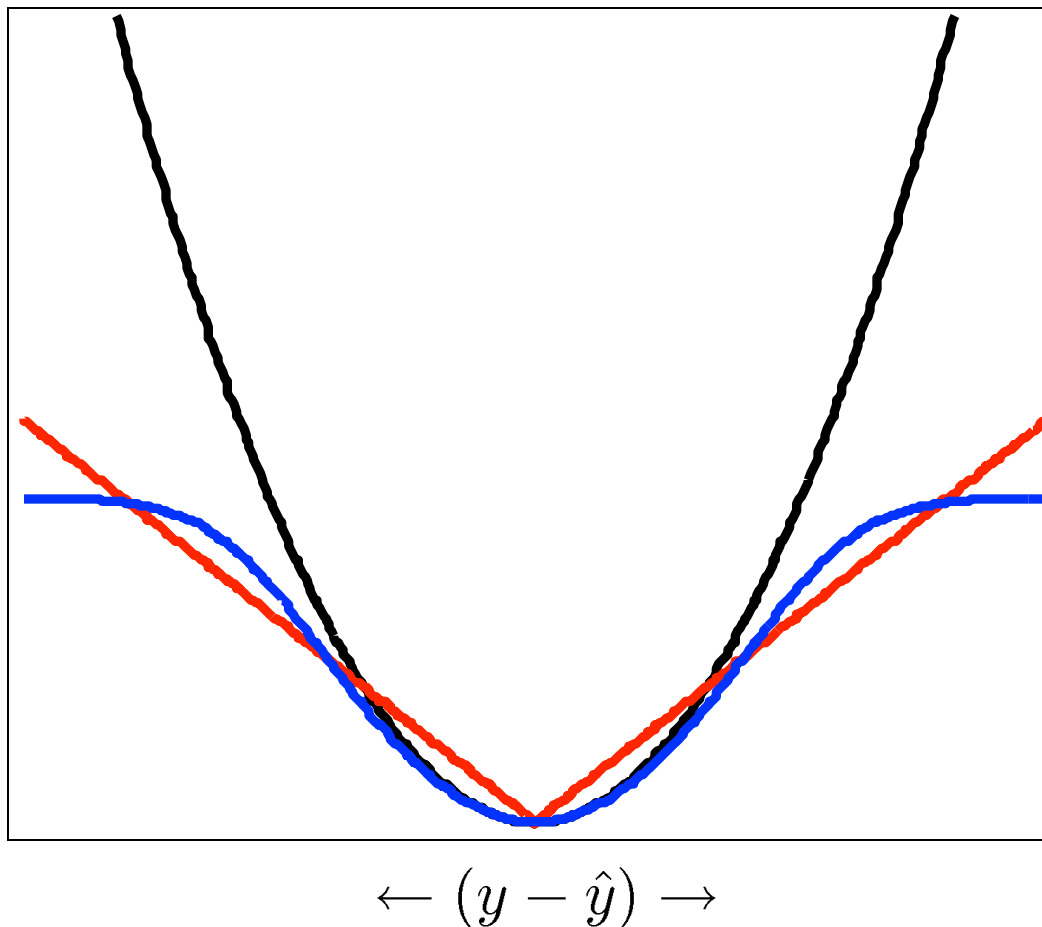
$$\ell_2 : (y - \hat{y})^2 \quad \text{(MSE)}$$

$$\ell_1 : |y - \hat{y}| \quad \text{(MAE)}$$

Something else entirely...

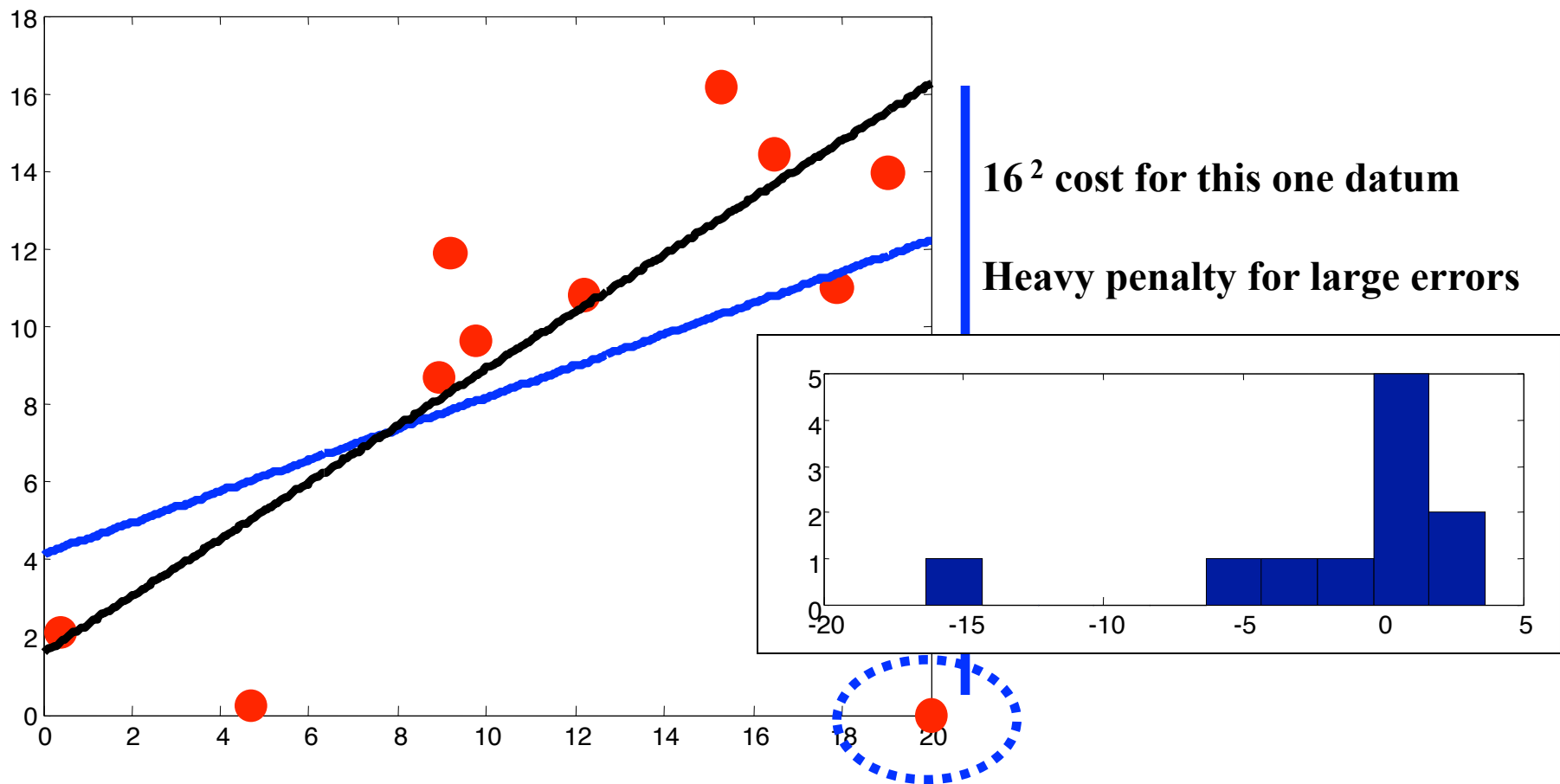
$$c - \log(\exp(-(y - \hat{y})^2) + c) \quad \text{(???)}$$

“Arbitrary” functions can’t be solved in closed form...
- use gradient descent

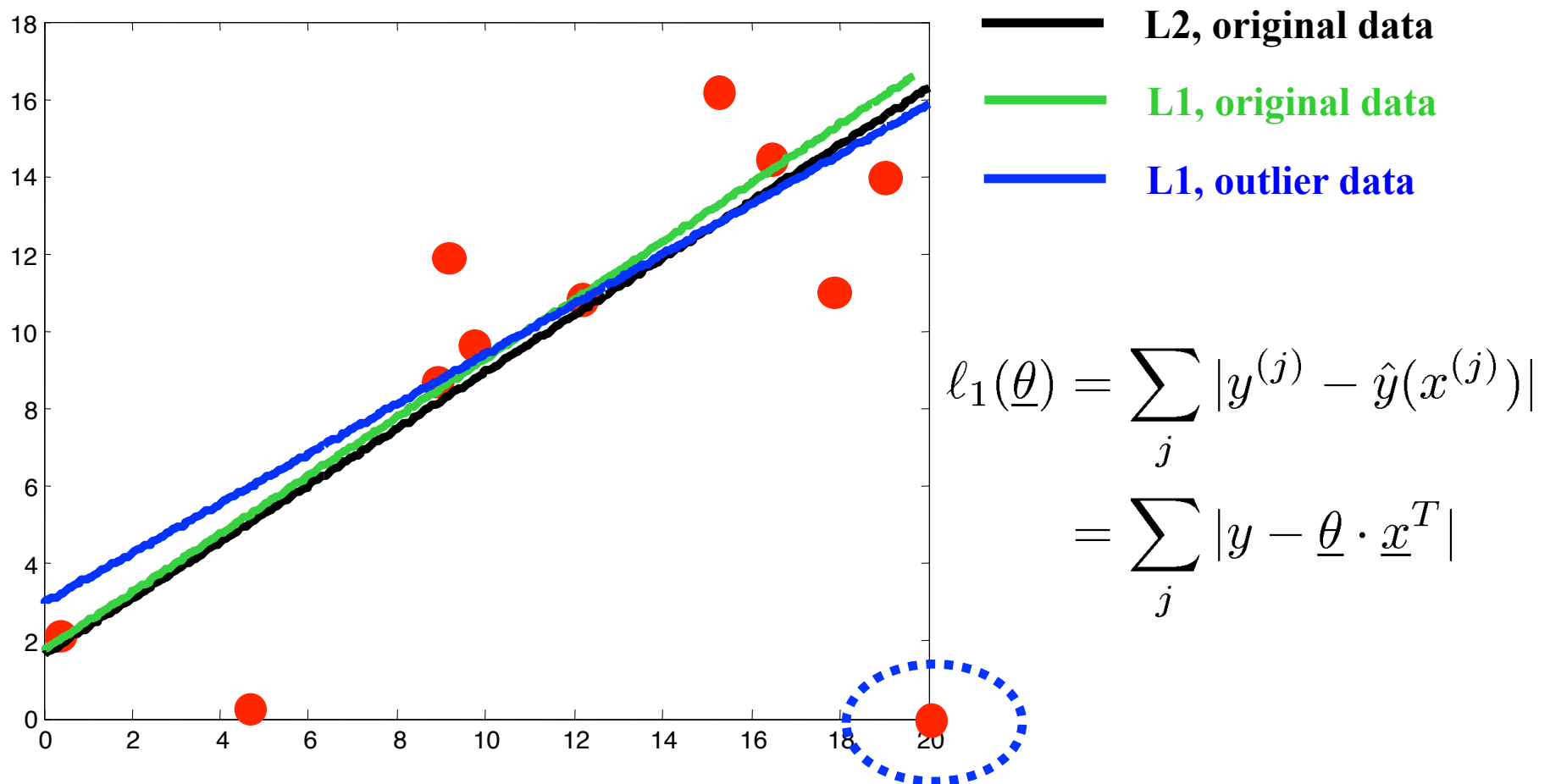


Effects of cost function choice

- Sensitivity to outliers

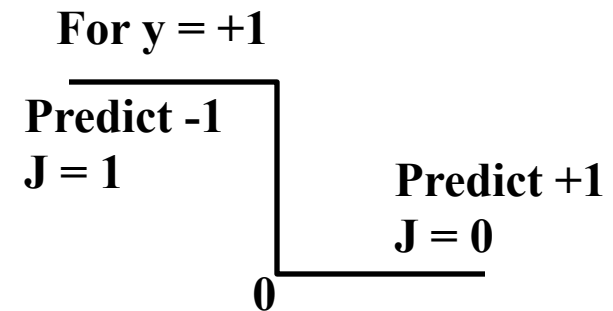


L1 error



Classification cost functions

- Consider a linear classifier
- $J(.) = \#$ of misclassified data?
 - Not smooth = hard to train



- This is called the 0/1 loss
 - Cost 0 when we're right; cost 1 when we're wrong
- Often, it's what we care about
 - Measures the number of mistakes we will make
- It's hard to optimize
 - No incentive to be "less wrong" or "more right"

Surrogate loss functions

- Replace 0/1 loss $J(\theta, x^{(i)}) = \delta(T(\theta x^{(i)}) \neq y^{(i)})$ with something easier:

- Logistic MSE

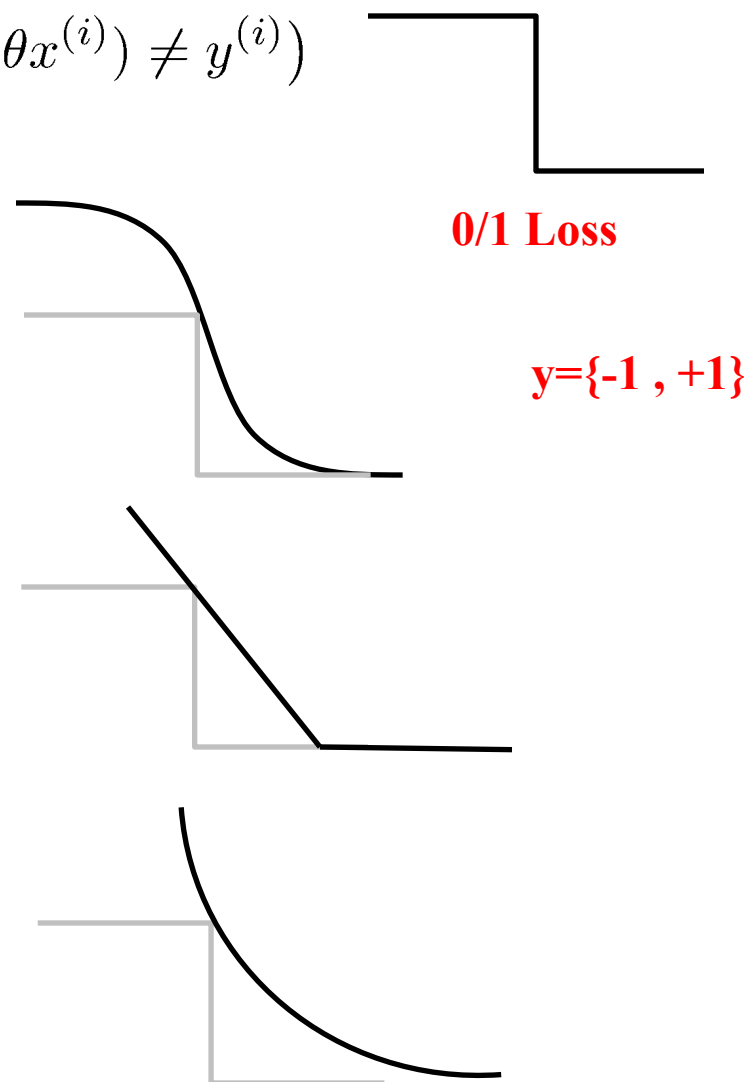
$$J(\theta, x^{(i)}) = (\sigma(\theta x^{(i)}) - y^{(i)})^2$$

- Hinge loss

$$J(\theta, x^{(i)}) = \max[0, 1 - y^{(i)} \theta x^{(i)}]$$

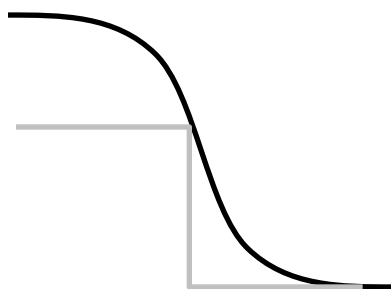
- Exponential loss

$$J(\theta, x^{(i)}) = \exp[-y^{(i)} \theta x^{(i)}]$$

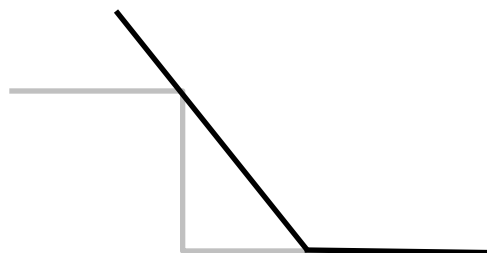


Surrogate loss functions

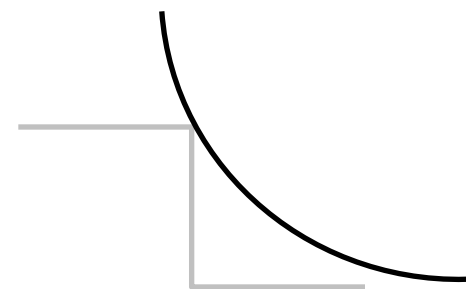
- Properties of a good loss function
 - Close to desired “real” loss?
 - Upper bound: low surrogate loss \Rightarrow low real loss
 - Smooth
 - Derivative = 0 only if real cost = 0
 - Convex?
 - Easy to optimize; no local optima



Logistic MSE



Hinge



Exponential