Loss Functions for Regression and Classification

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Regression Loss Functions

Loss Functions for Regression

- In general, loss function may take the form

$$(\hat{y}, y) \mapsto \ell(\hat{y}, y)$$

- Regression losses usually only depend on the **residual:**

$$r = y - \hat{y}$$

$$(\hat{y}, y) \mapsto \ell(r) = \ell(y - \hat{y})$$

- When would you **not** want a translation-invariant loss?
- Often you can transform your response y so it's translation-invariant. (e.g. log transform)

Some Losses for Regression

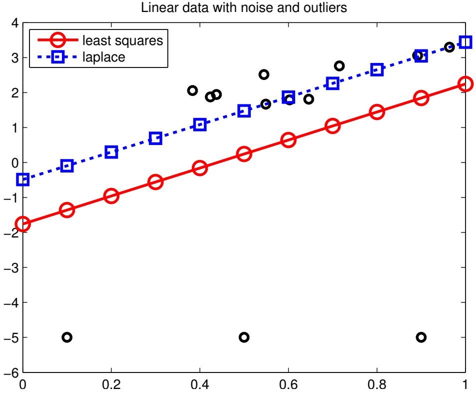
- **Square** or ℓ_2 Loss: $\ell(r) = r^2$
- **Absolute** or **Laplace** or ℓ_1 Loss: $\ell(r) = |r|$

$\hat{y}$	y	$\|r\| = \|y - \hat{y}\|$	$r^2 = (y - \hat{y})^2$
0	1	1	1
0	5	5	25
0	10	10	100
0	50	50	2500

KPM Figure 7.6

Loss Function Robustness

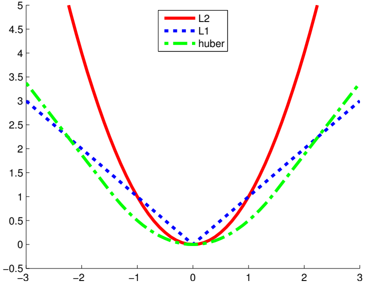
- **Robustness** refers to how affected a learning algorithm is by outliers.



KPM Figure 7.6

Some Losses for Regression

- **Square** or ℓ_2 Loss: $\ell(r) = r^2$ (not robust)
- **Absolute** or **Laplace** or ℓ_1 Loss: $\ell(r) = |r|$ (not differentiable)
  - gives **median regression**
- **Huber** Loss: Quadratic for $|r| \leqslant \delta$ and linear for $|r| > \delta$
  - robust and differentiable



KPM Figure 7.6

Classification Loss Functions

The Classification Problem

- Action space $\mathcal{A} = \{-1, 1\}$ Output space $\mathcal{Y} = \{-1, 1\}$
- **0-1 loss** for $f : \mathcal{X} \to \{-1, 1\}$:

$$\ell(f(x), y) = 1(f(x) \neq y)$$

- But let's allow real-valued predictions $f : \mathcal{X} \to \mathbf{R}$:

$$f > 0 \implies \text{Predict } 1$$
$$f < 0 \implies \text{Predict } -1$$

The Classification Problem: Real-Valued Predictions

- Action space $\mathcal{A} = \mathbf{R}$ Output space $\mathcal{Y} = \{-1, 1\}$
- Prediction function $f : \mathcal{X} \to \mathbf{R}$

Definition

The value $f(x)$ is called the **score** for the input x. Generally, the magnitude of the score represents the **confidence of our prediction**.

Definition

The **margin** on an example (x, y) is $yf(x)$. The margin is a measure of how **correct** we are.

- We want to **maximize the margin**.
- Most classification losses depend only on the margin.

The Classification Problem: Real-Valued Predictions

- Empirical risk for $0-1$ loss:

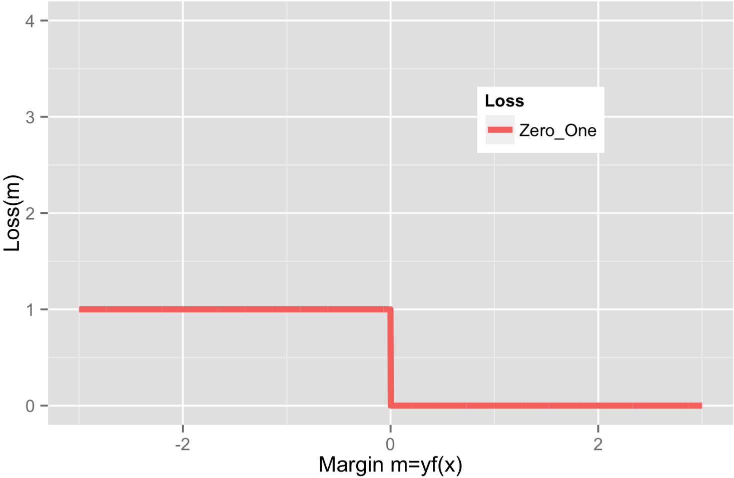
$$\hat{R}_n(f) = \frac{1}{n}\sum_{i=1}^{n} 1(y_i f(x_i) \leqslant 0)$$

Minimizing empirical $0-1$ risk not computationally feasible

$\hat{R}_n(f)$ is non-convex, not differentiable (in fact, discontinuous!).
Optimization is **NP-Hard**.

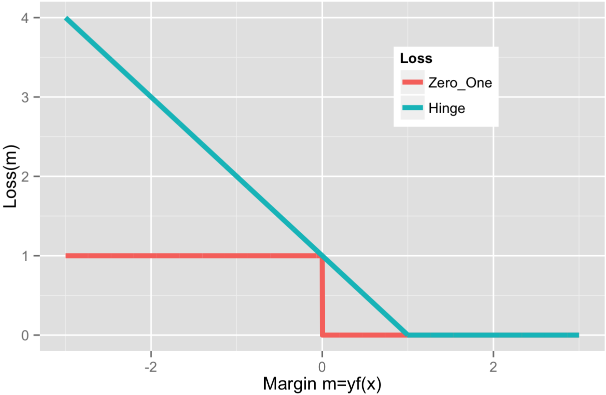
Classification Losses

Zero-One loss: $\ell_{0\text{-}1} = 1(m \leqslant 0)$



Classification Losses

SVM/Hinge loss: $\ell_{\text{Hinge}} = \max\{1-m, 0\} = (1-m)_+$



Hinge is a **convex**, **upper bound** on $0-1$ loss. Not differentiable at 1.
We have a **"margin error"** when $m < 1$.

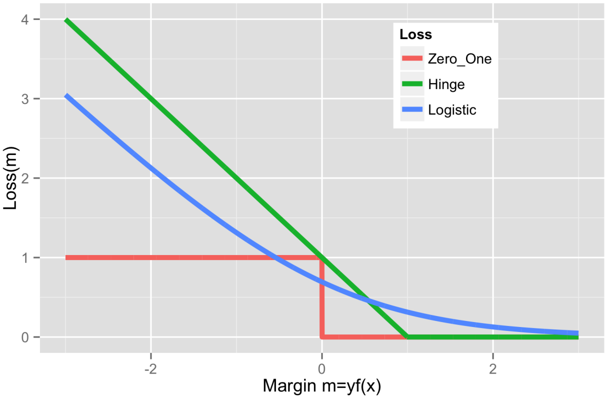
(Soft Margin) Linear Support Vector Machine

- Hypothesis space $\mathcal{F} = \left\{ f(x) = w^T x \mid w \in \mathbf{R}^d \right\}$.
- Loss $\ell(m) = (1-m)_+$
- ℓ_2 regularization

$$\min_{w \in \mathbf{R}^d} \sum_{i=1}^{n} (1 - y_i f_w(x_i))_+ + \lambda \|w\|_2^2$$

Classification Losses

Logistic/Log loss: $\ell_{\text{Logistic}} = \log\left(1 + e^{-m}\right)$



Logistic loss is differentiable. Never enough margin for logistic loss.

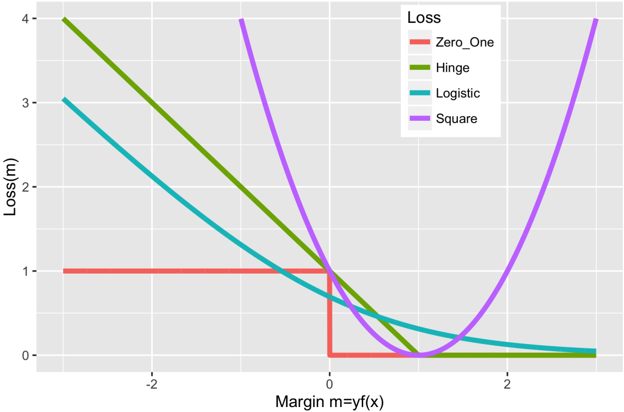
What About Square Loss for Classification?

- Action space $\mathcal{A} = \mathbf{R}$ Output space $\mathcal{Y} = \{-1, 1\}$
- Loss $\ell(f(x), y) = (f(x) - y)^2$.
- Turns out, can write this in terms of margin $m = f(x)y$:

$$\ell(f(x), y) = (f(x) - y)^2 = (1 - m)^2$$

- Prove using fact that $y^2 = 1$, since $y \in \{-1, 1\}$.

What About Square Loss for Classification?



Heavily penalizes outliers.

Seems to have higher sample complexity than hinge & logistic[1].

[1] Rosasco et al's "Are Loss Functions All the Same?" http://web.mit.edu/lrosasco/www/publications/loss.pdf