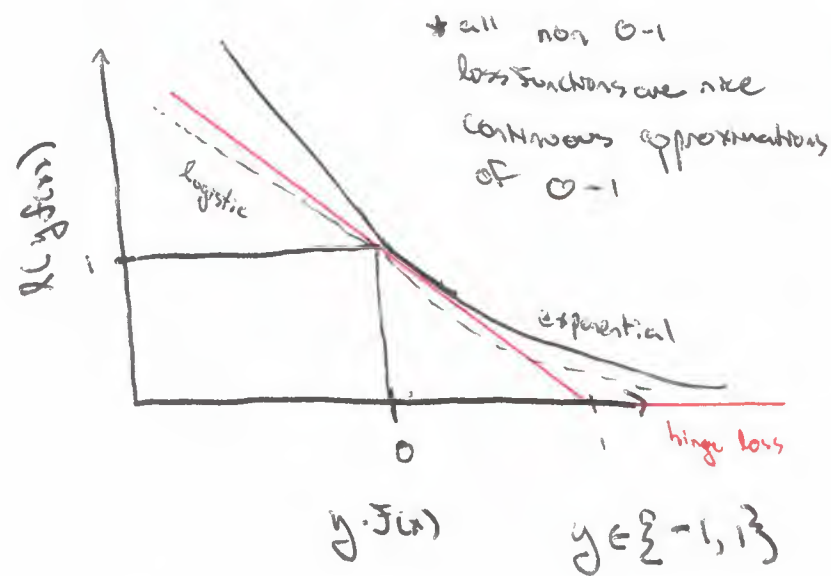


Loss Functions

• $F(x)$ is a signed "Score Function" and y is class label. Thus we want loss functions which penalize a lot for very negative values of $y \cdot F(x)$

• 0-1 (minimizes misclassification rate, but not differentiable at origin and has no gradient)

classification losses

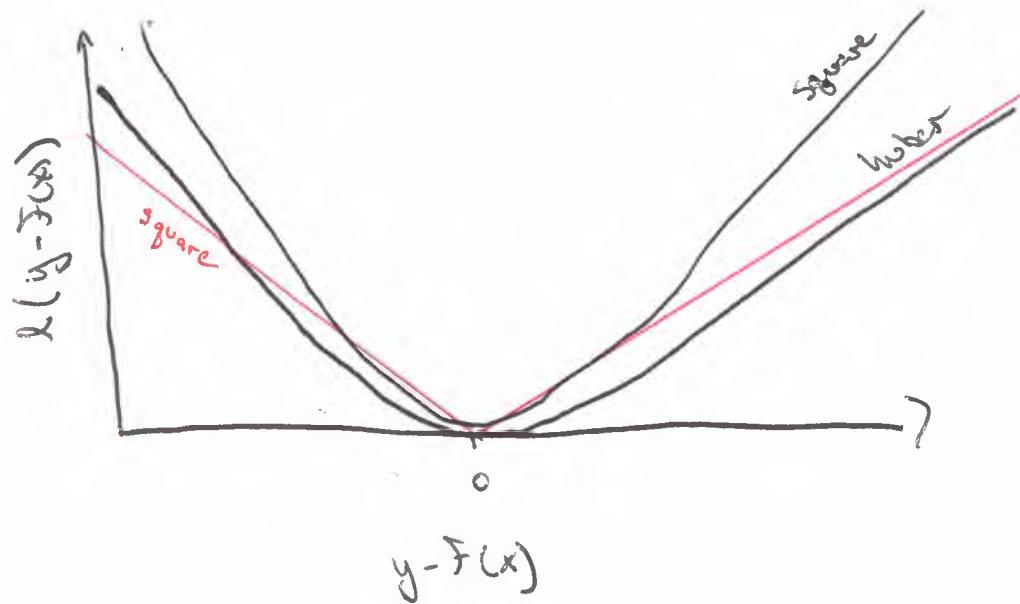


- exponential (nice theoretical properties, but increases exponentially so is sensitive to outliers)
- hinge (SVM loss)
- logistic (logistic regression loss)

• square (differentiable at origin, gradient slows down at origin which is helpful in gradient descent, but is sensitive to outliers since it increases quadratically).

• absolute (less sensitive to outliers since it increases linearly but, not differentiable at origin, and large gradient at origin).

regression losses



• huber (quadratic at origin and linear away from origin, the best of square and absolute loss, hence, 1 more hyperparameter, δ , to tune).

Some nice theoretical justifications for using l_2 and l_1 loss.

- the optimal prediction function using square loss results in predicting the conditional expected mean: $f^*(x) = E[Y|X=x]$

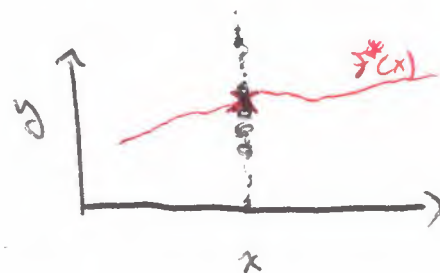
$$0 = \frac{d}{d\hat{y}} E[(Y - \hat{y})^2 | X] = \int \frac{d}{d\hat{y}} (y - \hat{y})^2 P(y|x) dy \Rightarrow \hat{y}^* = \int y P(y|x) dy = E[Y|X]$$

← minimal expected loss for each individual x

$$\Rightarrow \text{for each } x, \quad \boxed{f^*(x) = E[Y|X=x]}$$

← minimal expected loss for all x s

- using data, the prediction is thus the mean conditional estimator



- the optimal prediction function using absolute loss results in predicting the conditional median

$$0 = \frac{d}{d\hat{y}} E[|Y - \hat{y}| | X] = \int_{-\infty}^{\hat{y}} \frac{d}{d\hat{y}} (\hat{y} - y) P(y|x) dy + \int_{\hat{y}}^{\infty} \frac{d}{d\hat{y}} (y - \hat{y}) P(y|x) dy$$

$$\Rightarrow \int_{-\infty}^{\hat{y}^*} P(y|x) dy = \int_{\hat{y}^*}^{\infty} P(y|x) dy$$

\Rightarrow the only place this happens is at the median $\Rightarrow \hat{y}^* = \text{med}(P(y|x))$

$$\Rightarrow \boxed{f^*(x) = \text{med}(P(Y=y|X=x))}$$

- using data, the prediction is the median conditional estimator