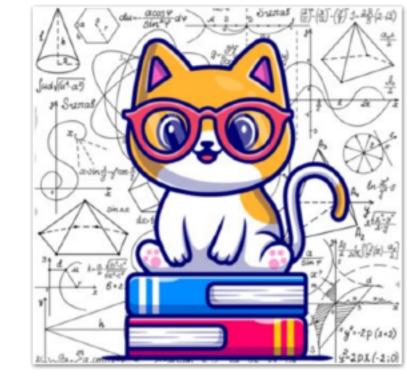
## Gradient Boosting Trees: The Math

$$z_i = -\frac{\partial Loss(y, F_i)}{\partial F_i}$$



## Negative Gradient of Loss w.r.t. Ensemble Prediction

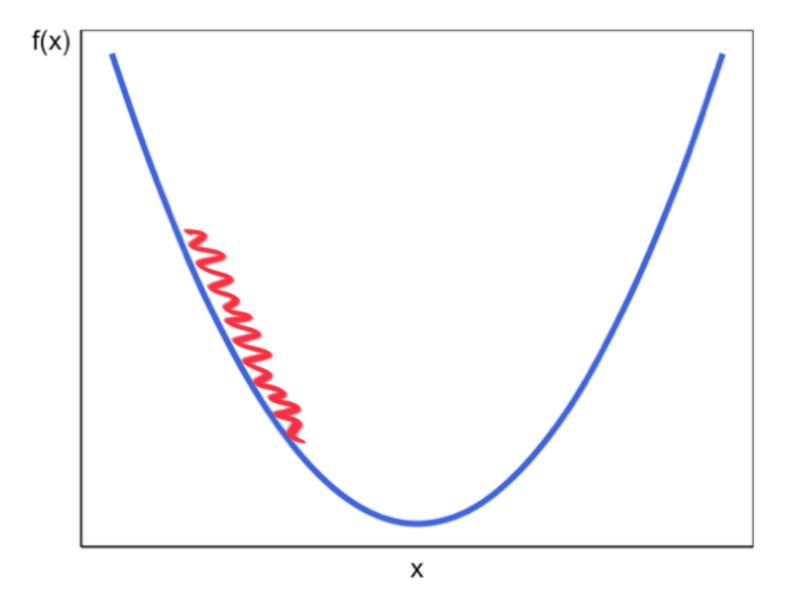
- ullet The Negative Gradient tell us what adjustments we should make to our prediction  $F_i$  in order to decrease our loss
- Example:

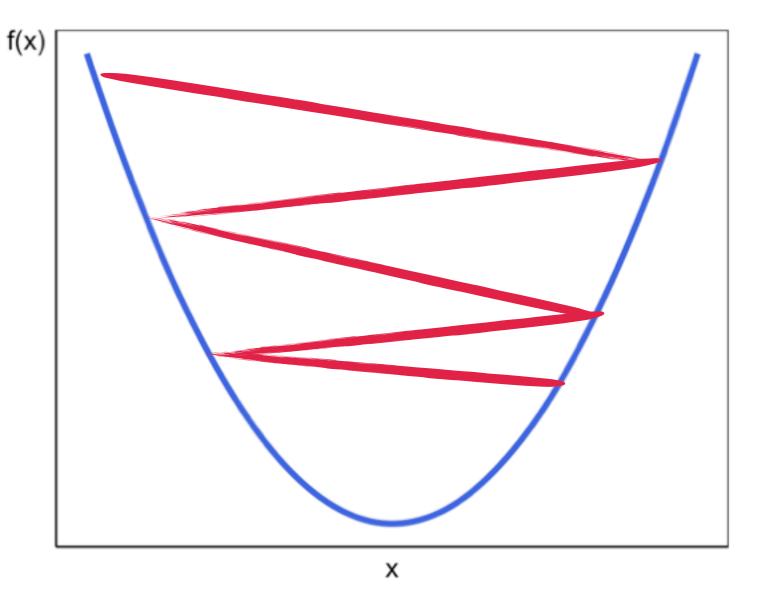
$$Loss(y, \hat{y}) = (y - \hat{y})^2 \implies -\frac{\partial Loss(y, \hat{y})}{\partial \hat{y}} \implies 2(y - \hat{y})$$

 With squared loss, error is the negative gradient, but the negative gradient will work in other situations!

## Choosing a Learning Rate: Convexity

- Under ideal conditions, gradient descent iteratively approximates and converges to the optimum
- For a constant learning rate  $\lambda$ 
  - $\blacktriangleright$  if  $\lambda$  is too small, it takes too many iterations to reach the optimum
  - $\blacktriangleright$  if  $\lambda$  is too large, algorithm may 'bounce' around the optimum and never get close





- Better to treat learning rate as a variable, that is let the value depend on gradient
- $\blacktriangleright$  around optimum  $\lambda$  is small, and far from optimum  $\lambda$  is larger