



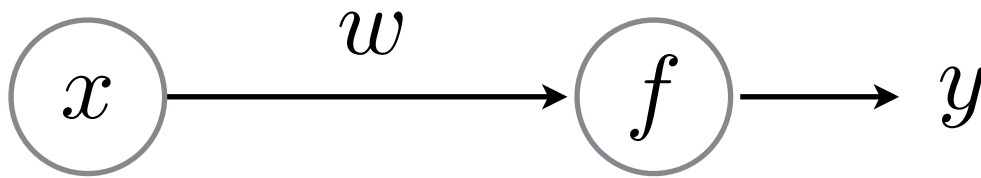
# How to Train Your Perceptron

Computer Vision

**Carnegie Mellon University (Kris Kitani)**

Let's start easy

# world's smallest perceptron!



$$y = wx$$

(a.k.a. line equation, linear regression)

# Learning a Perceptron

Given a set of samples and a Perceptron

$$\{x_i, y_i\}$$

$$y = f_{\text{PER}}(x; w)$$

Estimate the parameters of the Perceptron

$$w$$

Given training data:

$x$	$y$
10	10.1
2	1.9
3.5	3.4
1	1.1

*What do you think the weight parameter is?*

$$y = wx$$

Given training data:

$x$	$y$
10	10.1
2	1.9
3.5	3.4
1	1.1

*What do you think the weight parameter is?*

$$y = wx$$

not so obvious as the network gets more complicated so we use ...

# An Incremental Learning Strategy

(gradient descent)

Given several examples

$$\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$$

and a perceptron

$$\hat{y} = wx$$

# An Incremental Learning Strategy

(gradient descent)

Given several examples

$$\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$$

and a perceptron

$$\hat{y} = wx$$

Modify weight  $w$  such that  $\hat{y}$  gets **'closer'** to  $y$



# An Incremental Learning Strategy

(gradient descent)

Given several examples

$$\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$$

and a perceptron

$$\hat{y} = wx$$

Modify weight  $w$  such that  $\hat{y}$  gets '**closer**' to  $y$

perceptron  
parameter

perceptron  
output

true  
label

# An Incremental Learning Strategy

(gradient descent)

Given several examples

$$\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$$

and a perceptron

$$\hat{y} = wx$$

Modify weight  $w$  such that  $\hat{y}$  gets **'closer'** to  $y$

perceptron  
parameter

perceptron  
output

*what does  
this mean?*

true  
label

Before diving into gradient descent, we need to understand ...

## **Loss Function**

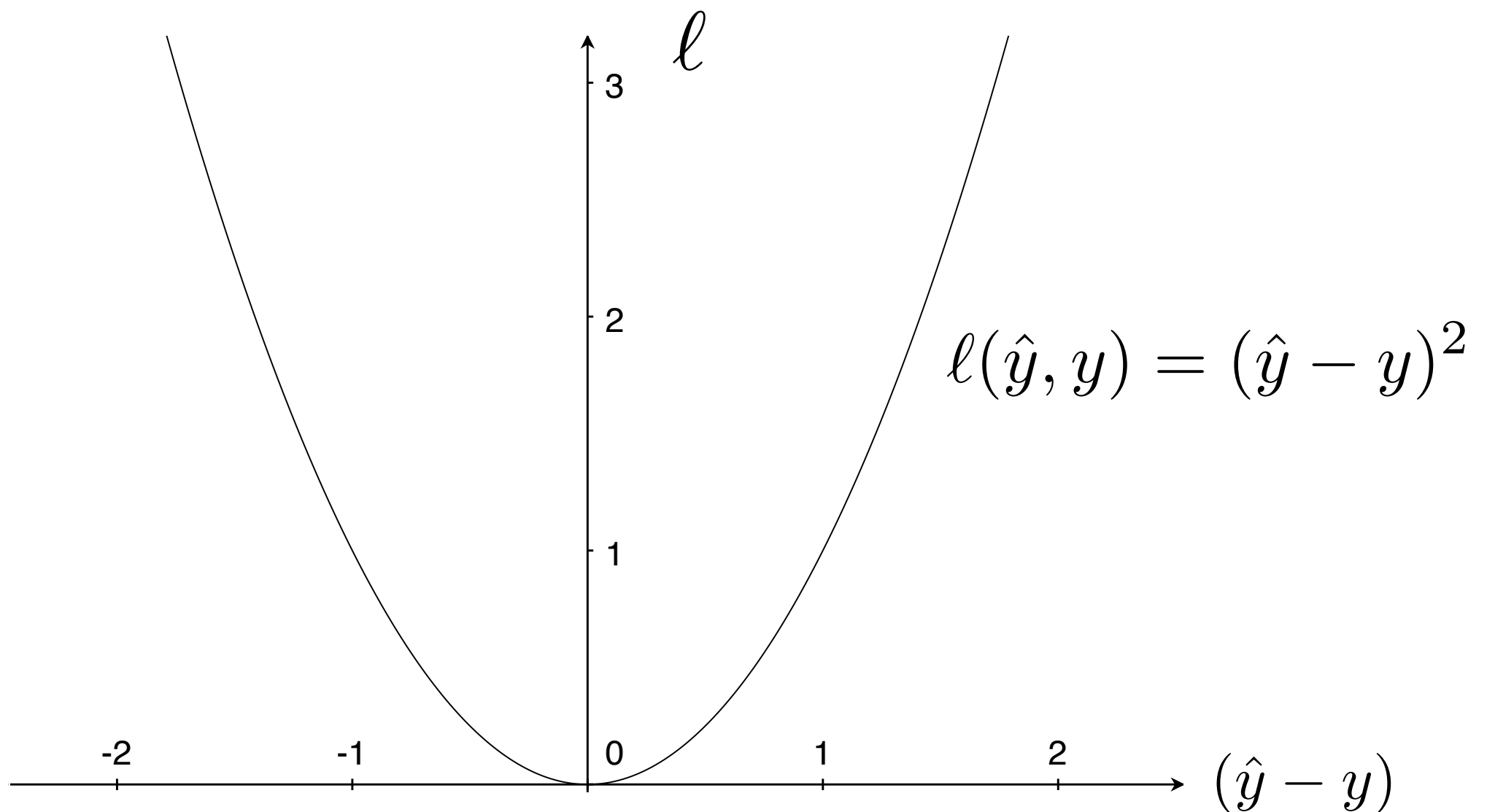
defines what it means to be  
**close** to the true solution

**YOU get to choose the loss function!**

(some are better than others depending on what you want to do)

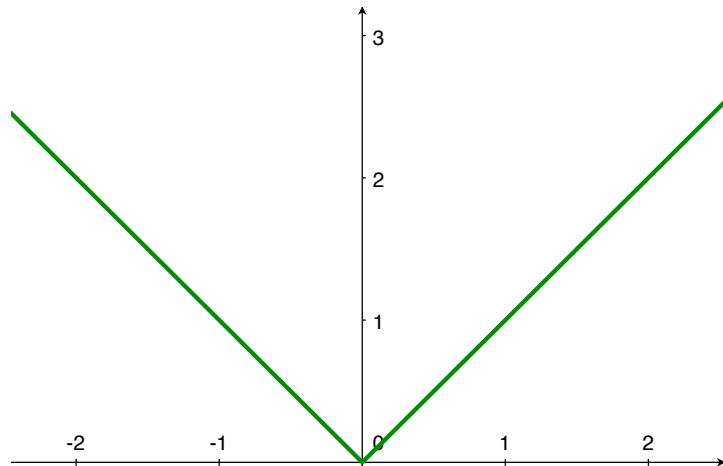
# Squared Error (L2)

(a popular loss function)



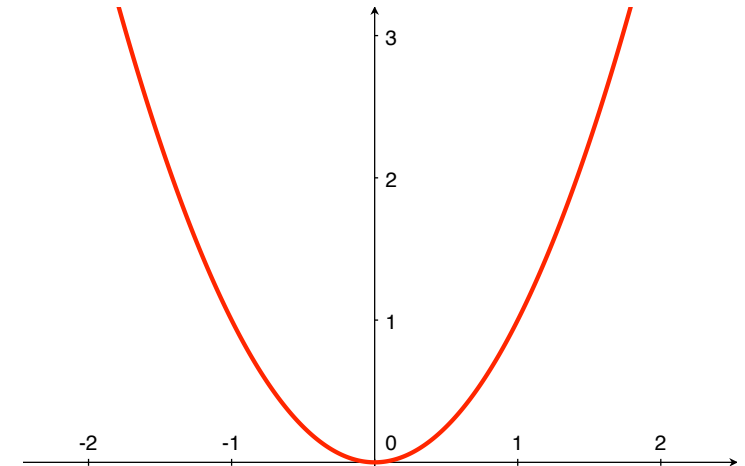
## L1 Loss

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



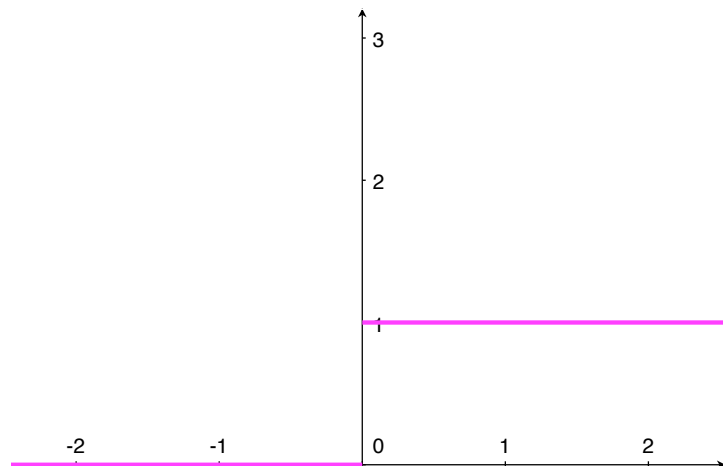
## L2 Loss

$$\ell(\hat{y}, y) = (\hat{y} - y)^2$$



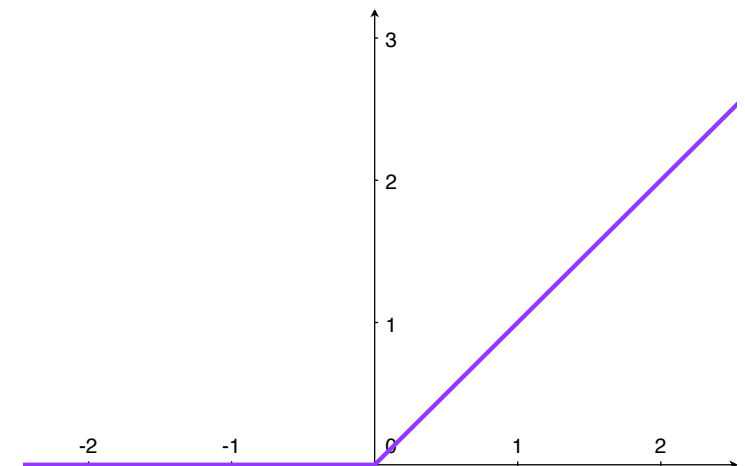
## Zero-One Loss

$$\ell(\hat{y}, y) = \mathbf{1}[\hat{y} \neq y]$$



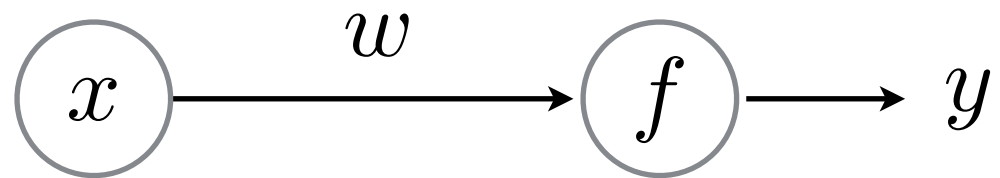
## Hinge Loss

$$\ell(\hat{y}, y) = \max(0, 1 - y \cdot \hat{y})$$



back to the...

# World's Smallest Perceptron!



$$y = wx$$

(a.k.a. line equation, linear regression)

function of **ONE** parameter!

# Learning a Perceptron

Given a set of samples and a Perceptron

$$\{x_i, y_i\}$$

$$y = f_{\text{PER}}(x; w)$$

*what is this*   
*activation function?*

Estimate the parameter of the Perceptron

$$w$$

# Learning a Perceptron

Given a set of samples and a Perceptron

$$\{x_i, y_i\}$$

$$y = f_{\text{PER}}(x; w)$$

*what is this  
activation function?*



linear function!  $f(x) = wx$

Estimate the parameter of the Perceptron

$$w$$



# Learning Strategy

(gradient descent)

Given several examples

$$\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$$

and a perceptron

$$\hat{y} = wx$$

Modify weight  $w$  such that  $\hat{y}$  gets '**closer**' to  $y$

perceptron  
parameter

perceptron  
output

true  
label

Let's demystify this process first...

Code to train your perceptron:

Let's demystify this process first...

Code to train your perceptron:

**for**  $n = 1 \dots N$

$w = w + (y_n - \hat{y})x_i;$

just one line of code!

Let's demystify this process first...

## Recall:

Code to train your perceptron:

for  $n = 1 \dots N$

$$w = w + (y_n - \hat{y})x_i;$$

just one line of code!

*Now where does this come from?*