

## < Bias and Variance - Learning Curve >

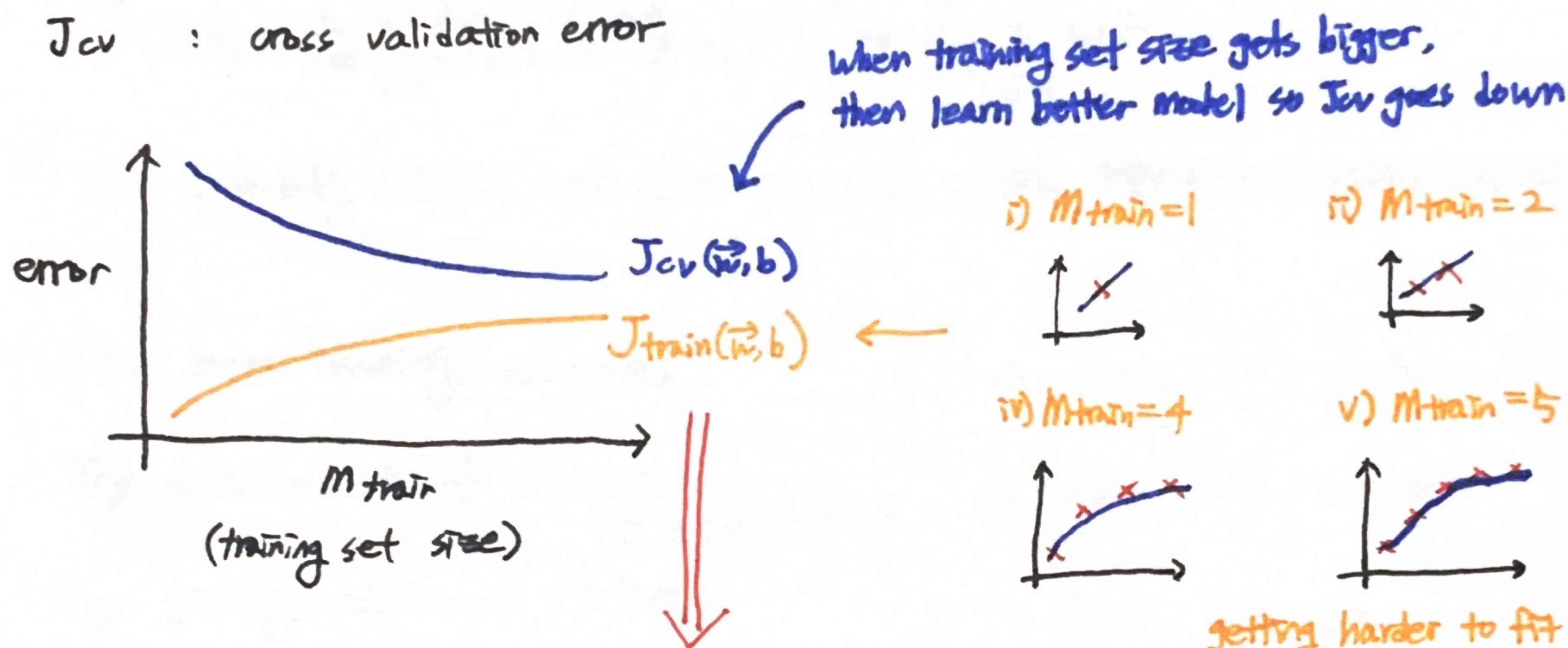
- learning curve: a way to help understand how your learning algorithm is doing as a function of the amount of experience it has  
ex) number of training example

ex)

$$\text{model: } f_{\vec{w},b}(x) = w_1 x + w_2 x^2 + b$$

$J_{\text{train}}$ : training error

$J_{\text{cv}}$ : cross validation error



i)  $M_{\text{train}}=1$



ii)  $M_{\text{train}}=2$



iii)  $M_{\text{train}}=3$



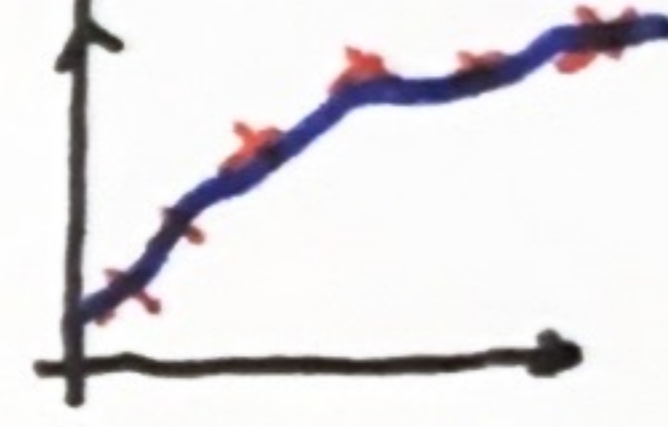
iv)  $M_{\text{train}}=4$



v)  $M_{\text{train}}=5$



vi)  $M_{\text{train}}=6$



getting harder to fit curve to train set  
 $\Rightarrow$  " $J_{\text{train}}$  increases"

$J_{\text{cv}}$  will be typically higher than  $J_{\text{train}}$

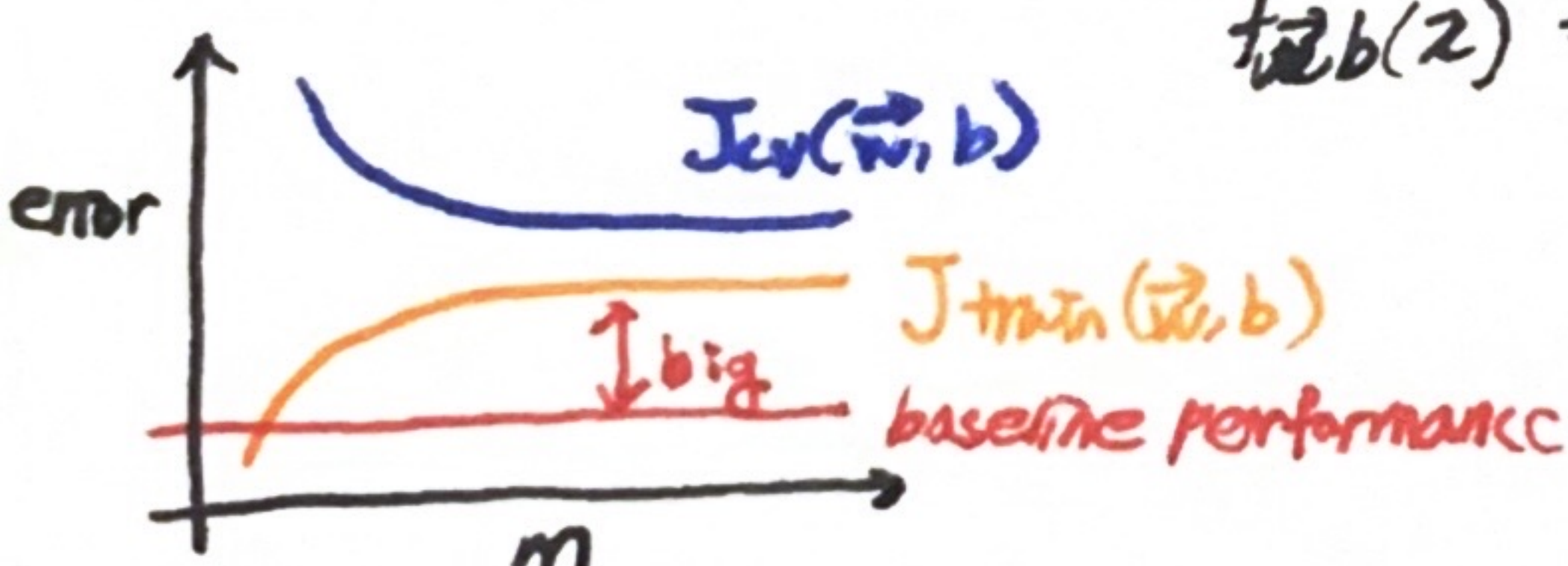
$\Rightarrow$  algorithm fit the parameter to train set

## \* Learning curve - high bias vs high variance

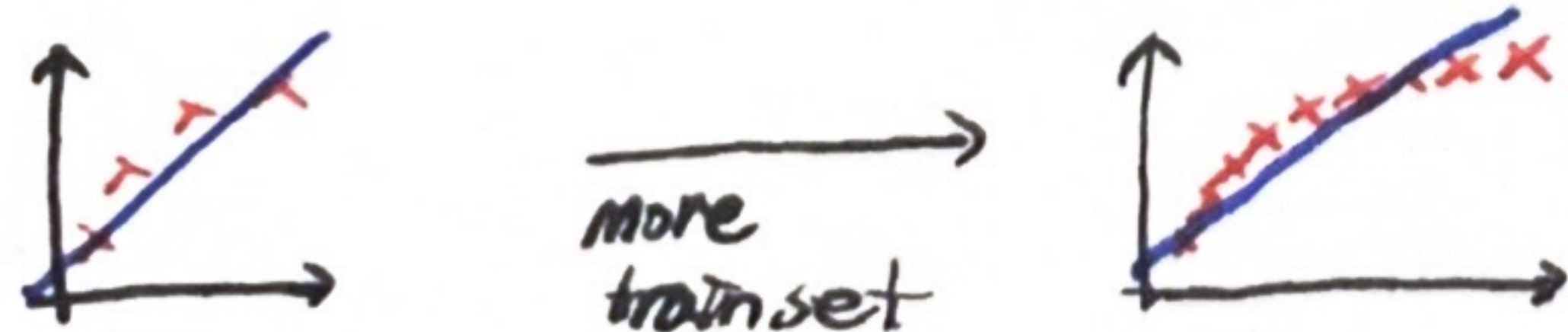
### ① High bias

ex) Model:

$$f_{\vec{w},b}(x) = w_1 x + b$$



$\Rightarrow$  if a learning algorithm suffers from high bias, getting more training data will not (by itself) help.



no matter how many more examples you add to this

figure straight line you're fitting

$\Rightarrow$  it isn't going to get that much better.

### ② High Variance

ex) Model:

$$f_{\vec{w},b}(x) = w_1 x + w_2 x^2 + w_3 x^3 + w_4 x^4 + b$$



$\Rightarrow$  if a learning algorithm suffers from high variance, getting more training data is likely to help

