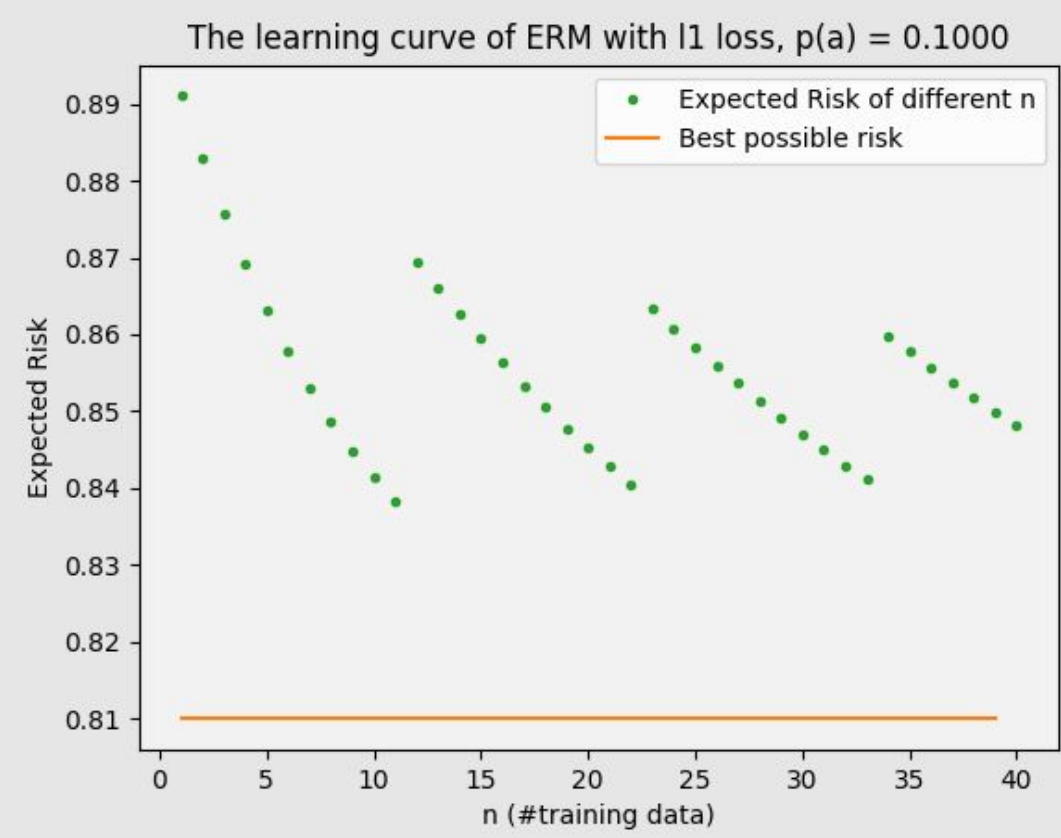
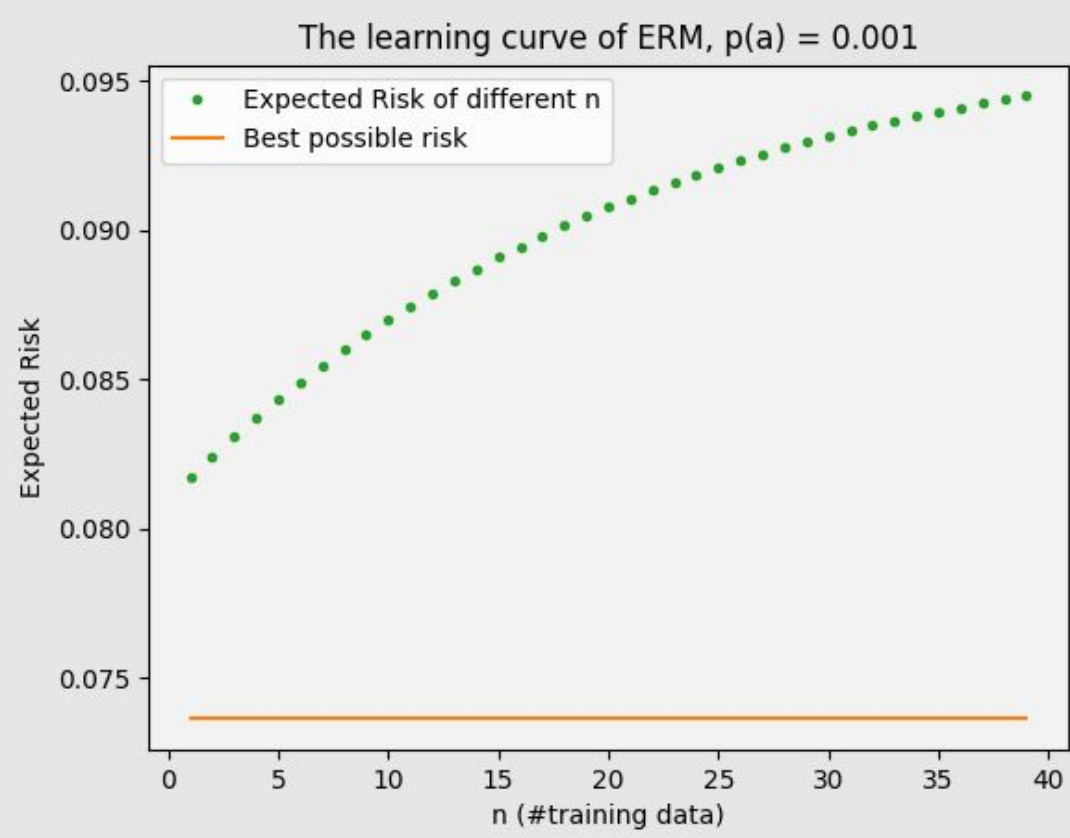


# More Data: Better or Worse

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## Why do the learning curves\* have unexpected behavior?

- Using  $ERM^*$ , Same distribution, but More data
- Hypothesis Class:  $\mathcal{H} = \{h(x) = \beta x | \beta \in \mathbb{R}\}$



### Problem Setting I

- Learner: ERM, L2 loss
- $\hat{R}(h) = \frac{1}{n} \sum_{i=1}^n (h(x_i) - y_i)^2$
- Distribution:
  - $a = (1, 1), b = (\frac{1}{10}, 1)$
  - $P(a) = 0.001, P(b) = 0.999$

### Problem Setting II

- Learner: ERM, L1 loss
- $\hat{R}(h) = \frac{1}{n} \sum_{i=1}^n |(h(x_i) - y_i)|$
- Distribution:
  - $a = (1, 1), b = (\frac{1}{10}, 1)$
  - $P(a) = 0.1, P(b) = 0.9$

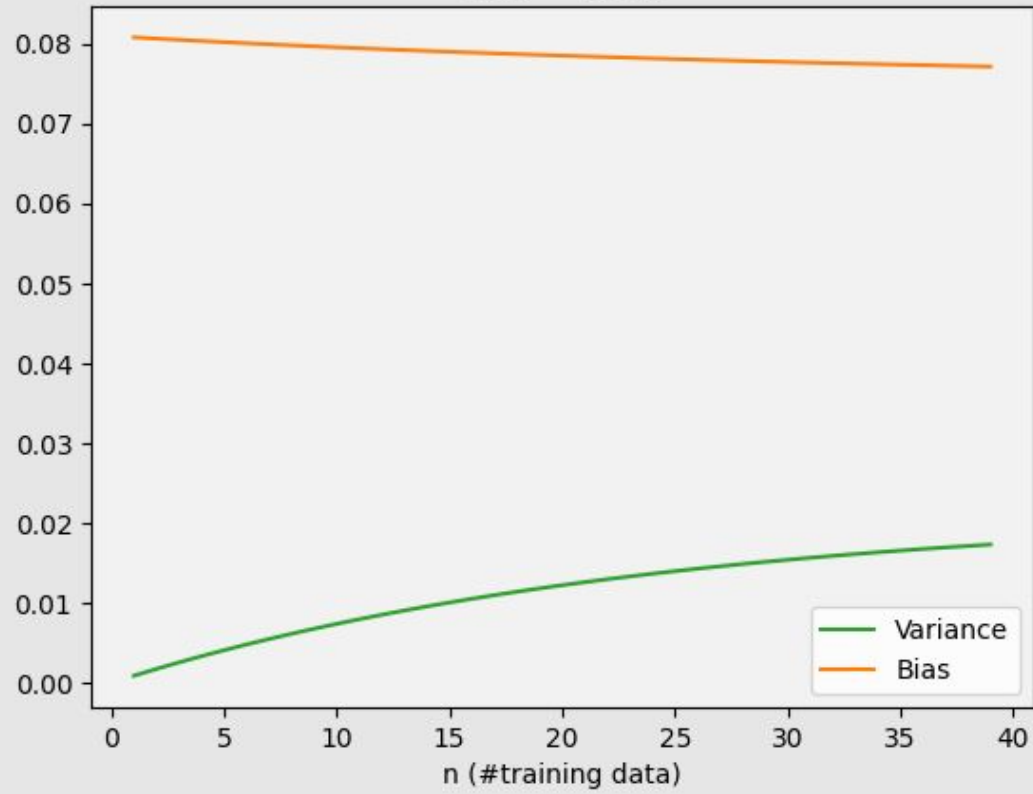
### Performance metrics:

$$\mathbb{E}_{S^n} \mathbb{E}_{(x,y)} (\hat{\beta}x - y)^2$$

### Bias-Variance trade-off:

$$\mathbb{E}_{S^n} \mathbb{E}_{(x,y)} (\hat{h}x - y)^2 = \underbrace{\mathbb{E}_x x^2 \text{Var}_{S^n}(\hat{h})}_{\text{variance}} + \underbrace{\mathbb{E}_x (\mathbb{E}_{S^n} \hat{h}x - 1)^2}_{\text{bias}}$$

Change of Bias and Variance term with respect to n, p(a) = 0.001

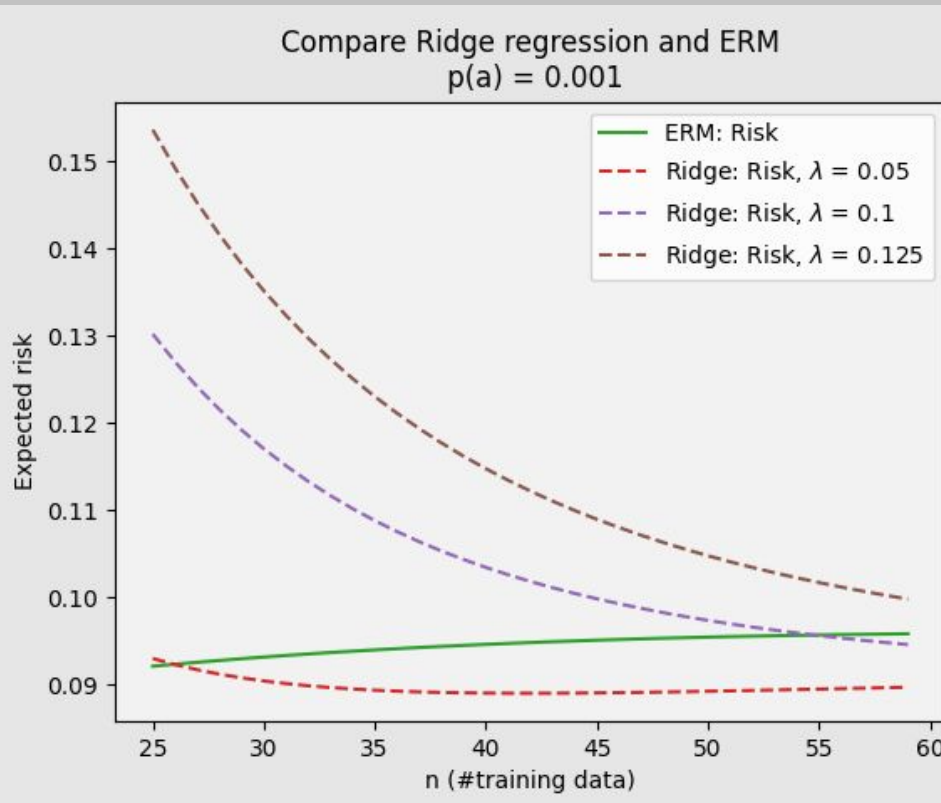
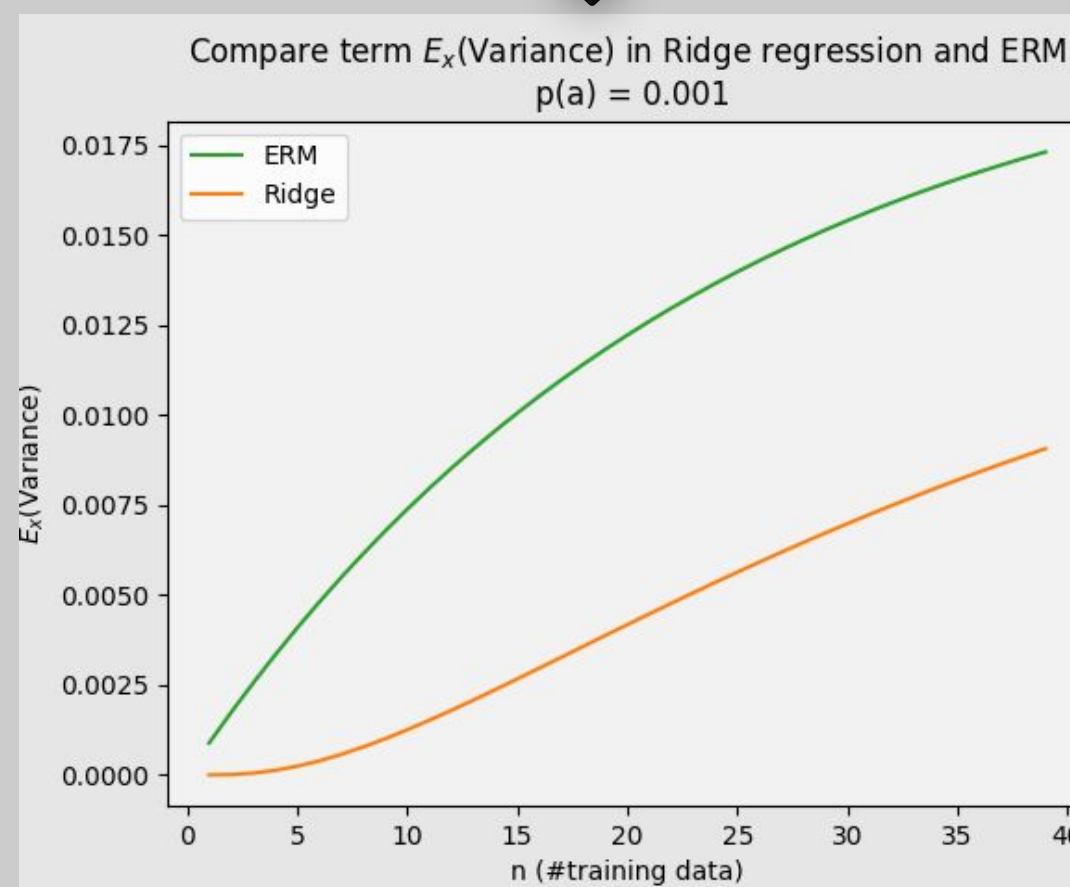


- Variance increases too fast
- Bias decreases too slow

### Increasing learning Curve?

#### Ridge Regression

$$A_{\text{ridge}}(S^n) = \arg \min_{h \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^n \mathcal{L}(h(x_i), y_i) + \lambda \|\beta\|$$



### Why does variance increase?

Since  $\text{Var}(X_n) = \frac{1}{n} \text{Var}(x)$

Not conforming with linear model\*?

$$Y = \beta X + \epsilon, \text{ where } \mathbb{E}\epsilon = 0$$

### Four-point distribution:

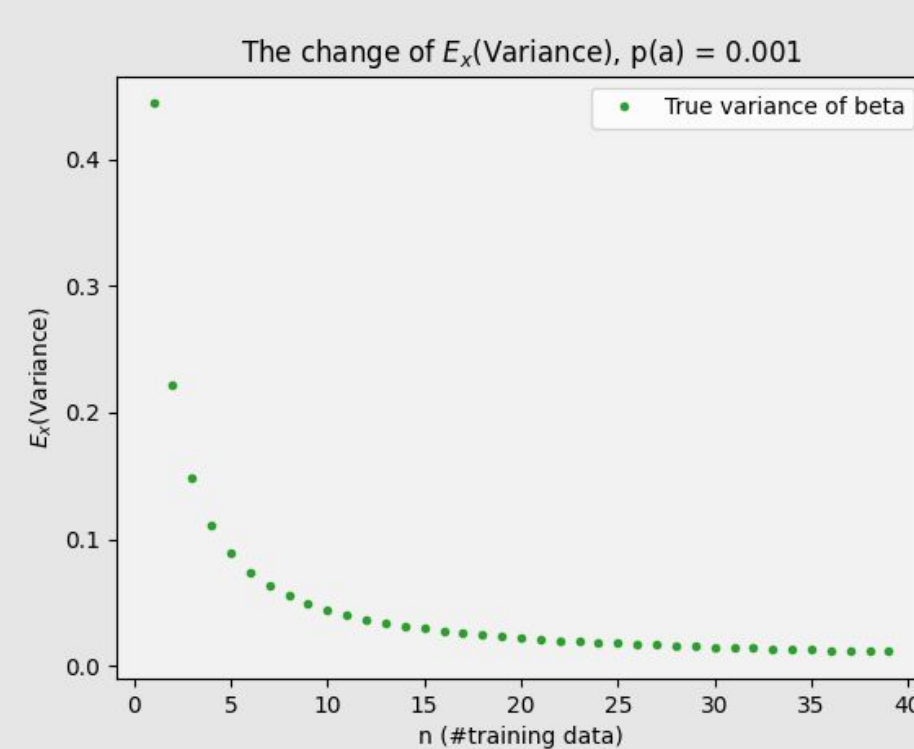
- $a_1 = [1, \frac{3}{2}], a_2 = [1, \frac{1}{2}], b_1 = [\frac{3}{4}, \frac{5}{4}], b_2 = [\frac{3}{4}, \frac{1}{4}]$
- $\frac{1}{2}p_a, \frac{1}{2}p_a, \frac{1}{2}p_b, \frac{1}{2}p_b$

### Fits linear model

$$Y = \beta X + \epsilon$$

$$\beta = 1, R_X = \left\{1, \frac{3}{4}\right\}$$

$$R_\epsilon = \left\{-\frac{1}{2}, \frac{1}{2}\right\}, P(\epsilon = \pm \frac{1}{2}) = \frac{1}{2}$$



### Result of ERM:

$$\hat{\beta} = \begin{cases} \frac{y_b}{x_b} & \text{if } n_a x_a - n_b x_b < 0 \\ \frac{y_a}{x_a} & \text{else} \end{cases}$$

### Best possible hypothesis:

$$\beta = \begin{cases} \frac{y_b}{x_b} & \text{if } P(a)x_a - P(b)x_b < 0 \\ \frac{y_a}{x_a} & \text{else} \end{cases}$$

### What is a learning curve?

- # training samples vs. generalization performance
- More training data? Better and worthy?

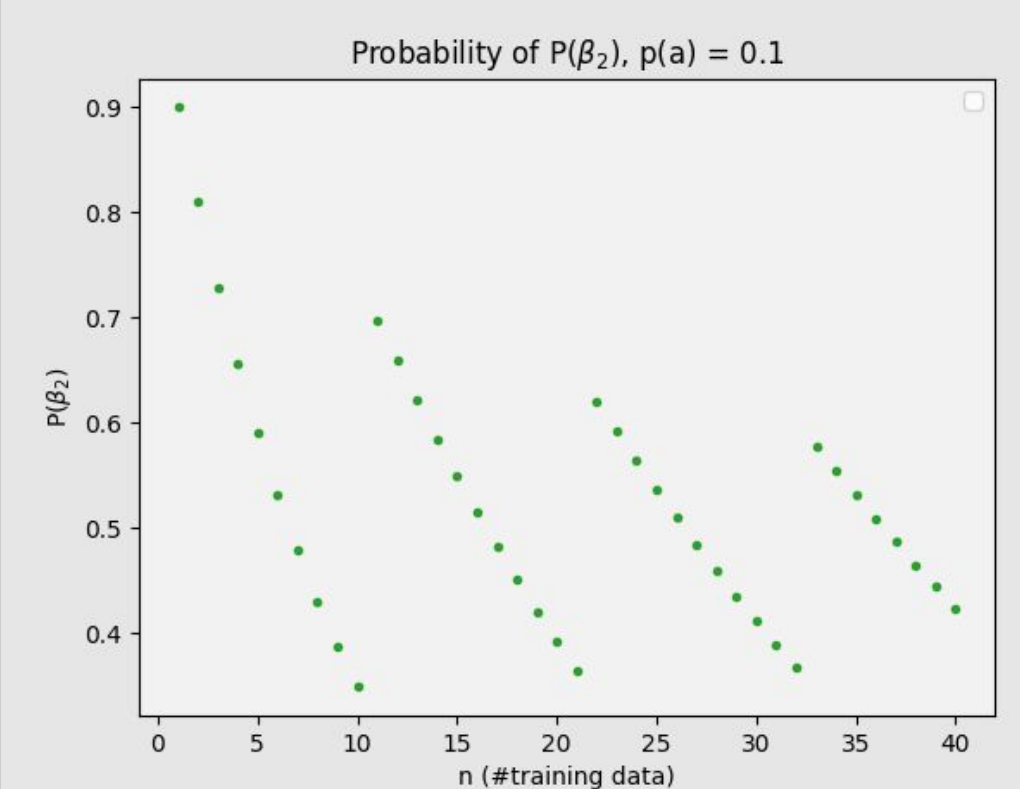
### What is ERM (Empirical Risk Minimizer)?

- Empirical Risk:
 
$$\hat{R}(h) = \frac{1}{n} \sum_{i=1}^n \mathcal{L}(h(x_i), y_i)$$
- Best hypothesis for training data
 
$$A_{\text{erm}}(S^n) = \arg \min_{h \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^n \mathcal{L}(h(x_i), y_i)$$

### Performance metrics:

Assume  $\hat{\beta}_1 = \frac{y_a}{x_a} = \beta, \hat{\beta}_2 = \frac{y_b}{x_b} \neq \beta$   
 Denote  $P(\hat{\beta} = \hat{\beta}_1)$  as  $P_1, P(\hat{\beta} = \hat{\beta}_2)$  as  $P_2$   
 $\mathbb{E}_{S^n} \mathbb{E}_{(x,y)} |\hat{\beta}x - y| = P_1 \cdot \mathbb{E}_{(x,y)} |\hat{\beta}_1(x) - y| + P_2 \cdot \mathbb{E}_{(x,y)} |\hat{\beta}_2(x) - y|$

The smaller  $P_2$  is, the smaller the risk is.



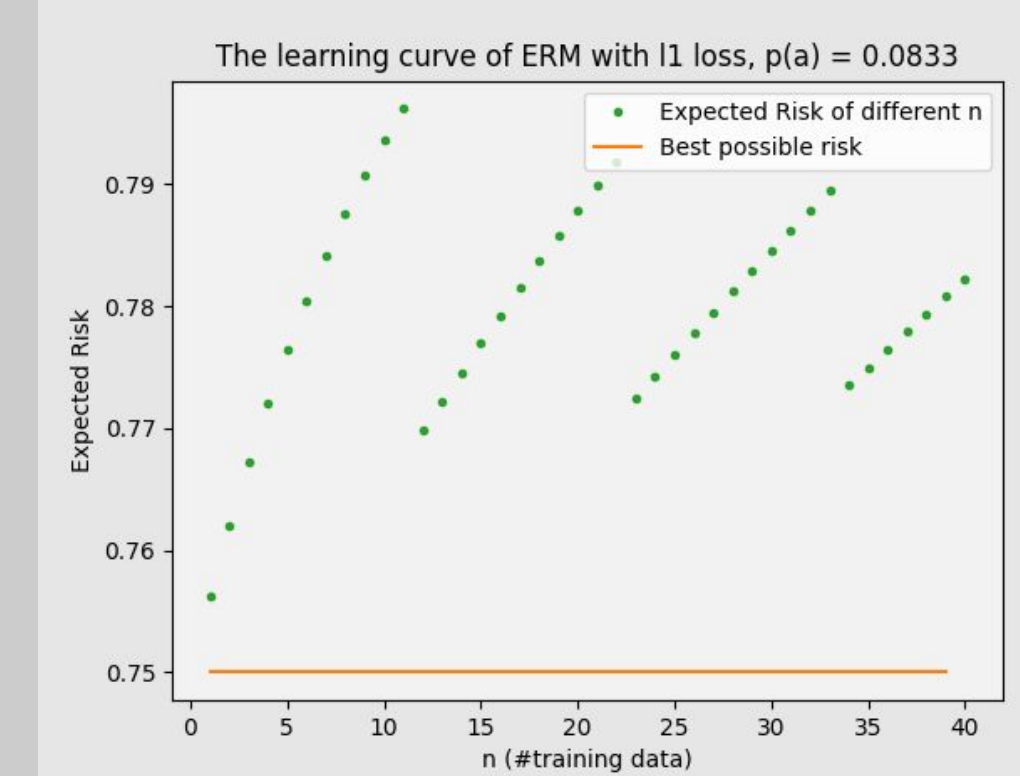
### What causes the periodic behavior?

If  $n_a x_a - n_b x_b < 0, \hat{\beta} = \frac{y_b}{x_b}$   
 Replace  $n_b$  with  $n - n_a, n_a < \frac{1}{\frac{x_a}{x_b} + 1} n$

$n_a, n \in \mathbb{N}$ , the possible value for  $n_a$  increases by 1 when  $n$  increases  $\lceil x_a/x_b + 1 \rceil$ , in this case 11.

### Can the learning curve change behavior?

- When  $\beta = \frac{y_b}{x_b}, P(a)x_a - P(b)x_b < 0$



- When  $\lceil x_a/x_b + 1 \rceil = 21$ :

