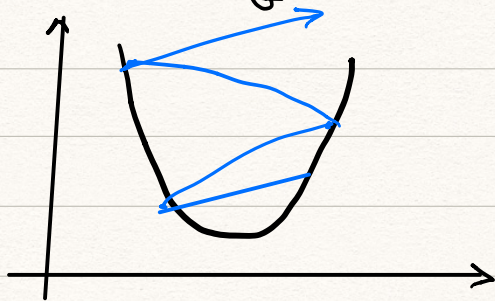


1-1. Large learning rate = overshooting

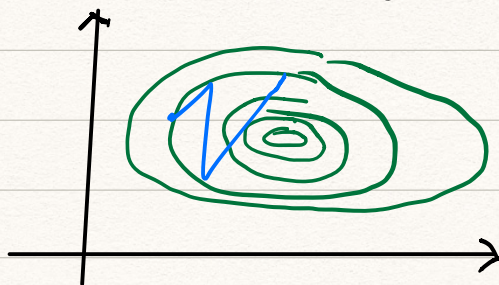


1-2. Small learning rate : takes too long, stops at local minimum



⇒ Try several learning rates

2. Data (X) preprocessing for gradient descent



	x_1	x_2	y
1	1	9000	A
2	2	-7000	A
4	4	-2000	B
6	6	8000	B
9	9	9000	C

데이터 값에 큰 차이가 있을 경우엔

'normalize' 해줄 필요가 있음.

많이 쓰는 방법은 $\left\{ \begin{array}{l} \text{zero-centered data 나} \\ \text{normalized data 도 됨.} \end{array} \right.$

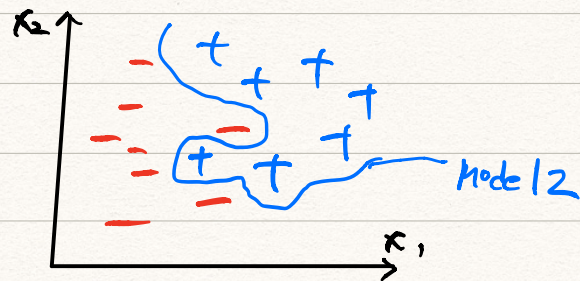
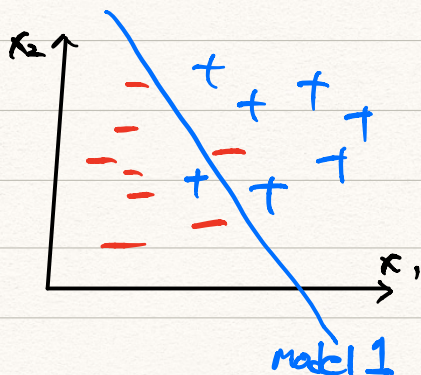
⊗ Standardization

$$x'_j = \frac{x_j - \mu_j}{\sigma_j} \quad \left. \vphantom{\frac{x_j - \mu_j}{\sigma_j}} \right] \text{차이}$$

$$x_std[:,0] = (x[:,0] - x[:,0].mean()) / x[:,0].std()$$

⊗ Overfitting

: 테스트에선 잘 맞으나, 실제에선 잘 안 맞는 모델.



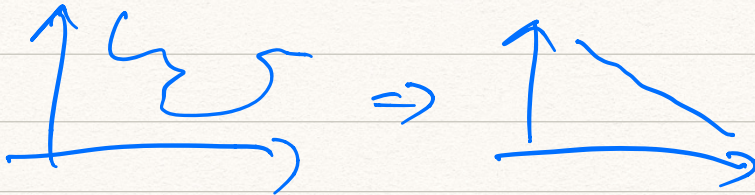
⇒ model 2는 저 상황에서 더 잘 맞지만, 실제 일반적인
상황에서는 잘 안 맞는 모델.
= Overfitting.

↳ training data가 많을수록 줄일 수 있어
{ features 수를 줄이자!
Regularization

⊛ Regularization

⇒ 너무 특정 상황에만 맞게 한정하지 말자.

- '구구리리' 말고 '표어'라.



$$\mathcal{L} = \frac{1}{N} \sum_i D(S(wx_i + b), L_i) + \lambda \sum w^2$$

regularization strength

`l2reg = 0.001 * tf.nn.reduce_sum(tf.nn.square(w))` 강도