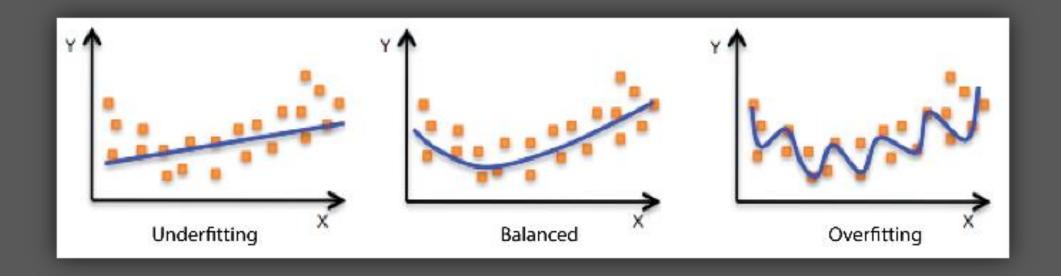


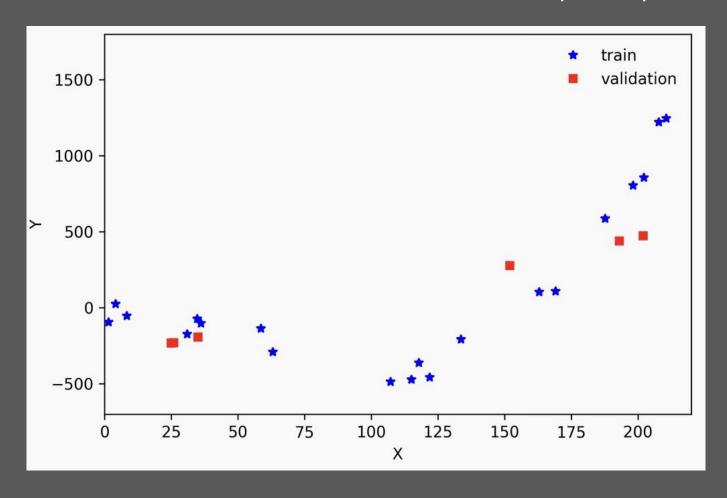
Discussion CAEsaaaaar



Recap

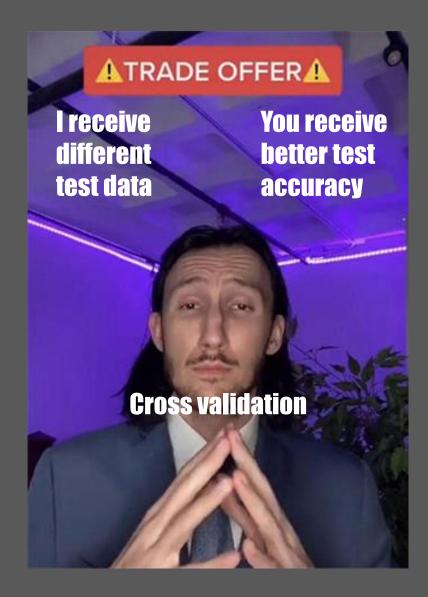


Motivation: we have validation dataset to measure how well the model is. But what if the validation dataset is poorly-chosen?



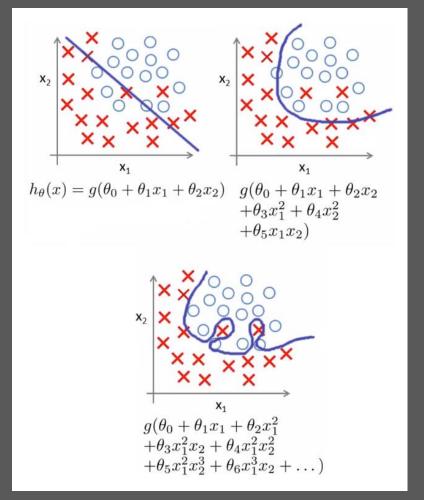
Solution: repeat the trials, change validation dataset, average accuracy across all trials





Recap: We can make the model more complex to capture non-linear data

Problem: What is the right degree complexity?



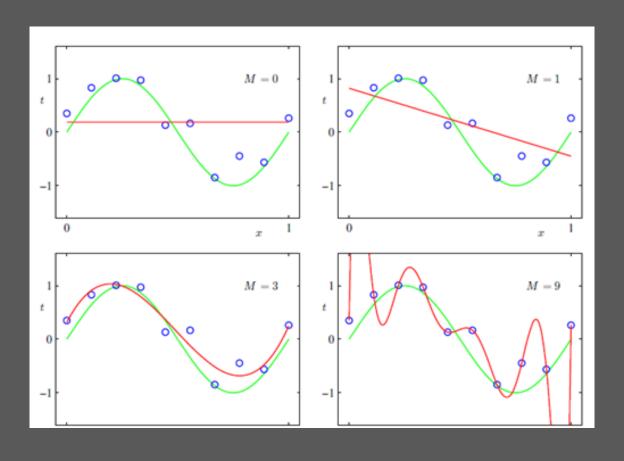
Solution:

Re



rization

Regularization

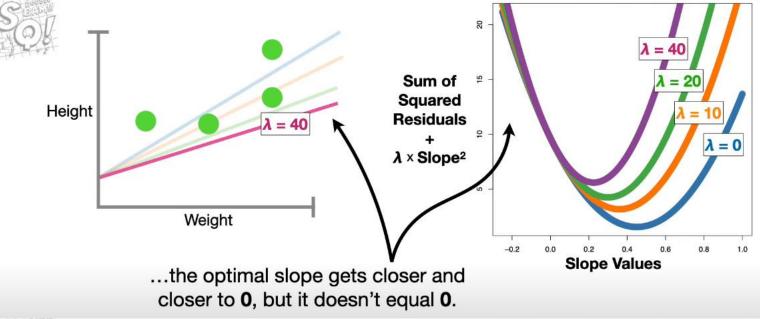


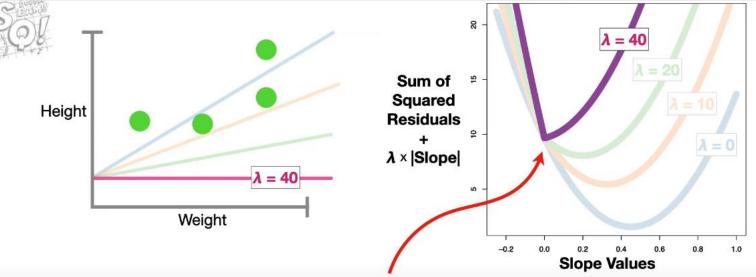
Key takeaway: We find a way to make the model underfits, so we can get higher testing accuracy even if training accuracy is low

Note: there is another type of regularization, which is called **Lasso**

The difference is that the penalty term, we use **absolute** instead of squaring the parameters

Ridge	Lasso
Squared the parameters	Take absolute of the parameters
Parameters get close to zero	Parameters can reach zero
Better when we believe every parameters are useful	Can exclude useless parameters





Now the lowest point in the purple curve, aka, the optimal slope given the Absolute Value Penalty when $\lambda = 40$, is 0.

Statquest Youtube video: Ridge vs Lasso Regression, Visualized!!!

https://www.youtube.com/watc
h?v=Xm2C_gTAl8c

But you know, I learned something today



- We use cross validation to average models across all trials, instead of accidentally pick the invalid test data
- We use ridge/lasso regression to lower training accuracy, but get higher test accuracy