

Motivation

- So far, to us, "model complexity" has essentially meant "number of features."

 The main hyperparameter we've tuned is polynomial degree. For instance, a polynomial of degree 5 has 5 features an x, x^2 , x^3 , x^4 , and x^5 feature.

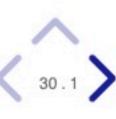
 In the more recent example, we **manually** created several different pipelines, each of which used different combinations of features from the commute times dataset.
- Once we've created several different candidate models, we've used cross-validation to choose the one that best generalizes to unseen data.
- Another approach: instead of manually choosing which features to include, put some constraint on the optimal parameters, $w_0^*, w_1^*, \ldots, w_d^*$.

 This would save us time from having to think of combinations of features that might be relevant.
- Intuition: The bigger the optimal parameters w_0^*, w_1^* , . (w_d^*) are, the more overfit the model is to the training data.

$$H(x) = 1 + 2x + 1000x^3 - 1000000x^9$$

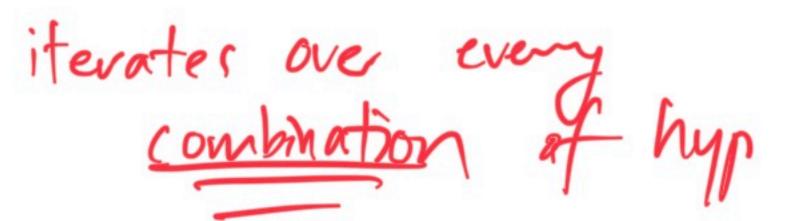
=) change x a little, output changes a lot!!!!

not good!





An easier approach: GridSearchCV

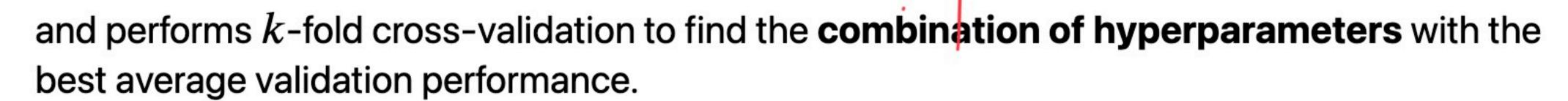


• Instead of having to for-loop over possible hyperparameter values, we can let sklearn do

the hard work for us, using GridSearchCV.

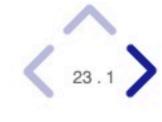


- an un-fit instance of an estimator, and
- a dictionary of hyperparameter values to try, //...



In [27]: from sklearn.model_selection import GridSearchCV

Why do you think it's called "grid search"?

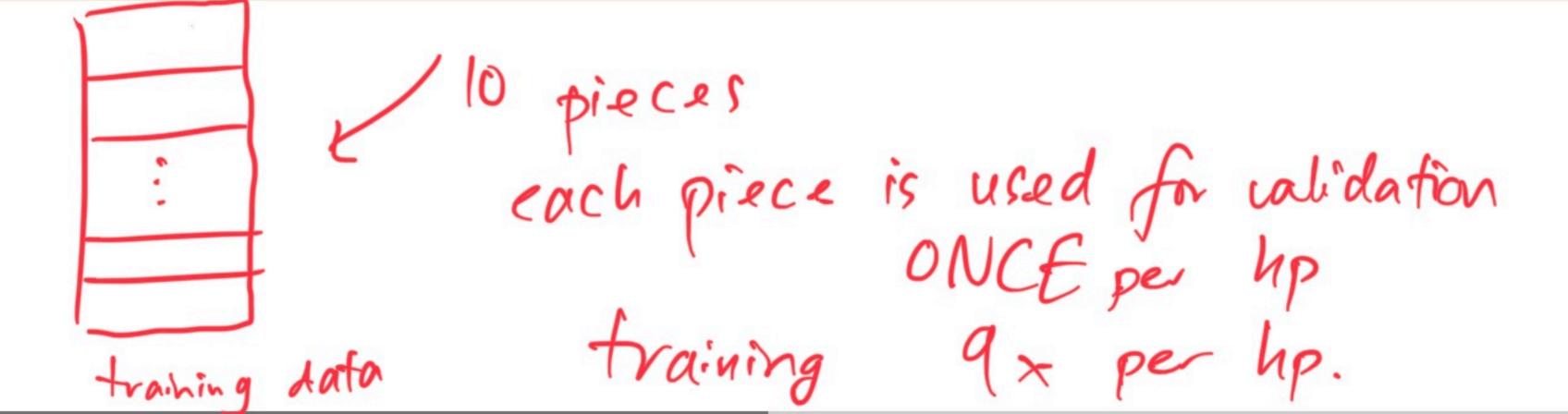




per hyperparameter: each point is used for training 9x = 20 hyperparams, 20 × 9 = [180]

Question (4) (Answer at practicaldsc.org/q)

- Suppose you have a training dataset with 1000 rows.
- You want to decide between 20 hyperparameters for a particular model.
- To do so, you perform 10-fold cross-validation.
- How many times is the first row in the training dataset (X.iloc[0]) used for training a model?



?