# **Cross-Validation**

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Oct 6, 2015



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## Motivation

In ridge regression, the parameter  $\lambda > 0$  can be tuned to reduce overfitting by reducing model complexity.

$$\min_{\beta} \quad \frac{1}{2N} \sum_{n=1}^{N} [y_n - \widetilde{\boldsymbol{\phi}}(\mathbf{x}_n)^T \boldsymbol{\beta}]^2 \quad + \quad \frac{\lambda}{2N} \sum_{j=1}^{M} \beta_j^2$$

But how do we choose  $\lambda$ ?

# The generalization error

The generalization error of a learning method is the expected prediction error for *unseen* data, i.e. mistakes made on the data that we are going to see in the future. This quantifies how well the method *generalizes*.

# Simulating the future

Ideally, we should choose  $\lambda$  to minimize the mistakes that will be made in the future. Obviously, we do not have the future data, but we can always *simulate the future* using the data in hand.

# Splitting the data

For this purpose, we split the data into train and validation sets, e.g. 80% as training data and 20% as validation data. We pretend that the validation set is the future data. We fit our model on the training set and compute a prediction-error on the validation set. This gives us an *estimate* of the generalization error (one instant of the future).

We plot estimates of the generalization error for many values of  $\lambda$  (grid search). We can then repeat this process for many random splits to  $\Im$  obtain confidence in our estimate.



Validation

Validatin error

or sim

foct, ex

use average RMSB.

Training

Train error

To chuose

Figure 1: The left figure shows ridge regression results for a 50-50 split. The right one shows a comparison with and without feature transformations. The improvement is very little and might be insignificant.

## **Cross-validation**

Random splits are not the most efficient way to compute the error.

K-fold cross-validation allows us to do this efficiently. We randomly partition the data into K groups. We train on K - 1 groups and test on the remaining group. We repeat this until we have tested on all K sets. We then average the results.



Cross-validation returns an unbiased estimate of the *generalization error* and its variance.

Question!

RMSE

### **Additional Notes**

#### Pseudo code for CV

```
1 % given K splits (yk, Xk)
2
 for i = 1:length(vals)
3
      lambda = vals(i);
      for k = 1:K
4
           % Compute beta for subgroups other than k
5
           beta = \dots
\mathbf{6}
           % train & test error on k'th subgroup
7
           errTrSub(k) = computeCost(yk, Xk, beta);
8
           errTeSub(k) = computeCost(yk, Xk, beta);
9
      end
10
      % compute average of train and test errors
11
      errTr(i) = mean(errTrSub(k));
12
      errTe(i) = mean(errTeSub(k));
13
14 end
15
  [errStar, lambdaStar] = min(errTe);
```

#### To do

- Implement CV and gain experience to set  $\lambda$  and K.
- Details on unbiasedness of cross-validation is in Section 7.10 in the book by Hastie, Tibshirani, and Friedman (HTF).
- Read about bootstrap in Section 7.11 in HTF book. This method is related to random splitting and is a very popular method.