Regularized Linear Regression

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Regularization

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- ***Regularization*** is a general method to avoid such overfitting by applying additional constraints to the weight vector
- A common strategy is to make sure that the weight are, on average, small in magnitude, which is known as ***shrinkage***

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- Let A be a learning algorithm, $S = (z_i, \ldots, z_m)$ be a training set of m examples and $A(S)$ denote the output of A
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- Thus, our interest is in the expectation

$$\mathbb{E}_s[L_{\mathfrak{D}}(A(S)) - L_s(A(S))$$

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- In this case, stability can be defines as: let z' be an additional example and $S^{(i)}$ be the training set obtained by replacing the i^{th} example of S,
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- Thus, stability measures the effect of the small change of the input on the output of A by comparing the loss of the hypotheses $A(S)$ on z_i to the loss of the hypotheses $A(S(^{(i)}))$ on z_i.
- Consequently, a good learning algorithm will have $\ell(A(S^{(i)}), z_i) - \ell(A(S), z_i) \geq 0$, since in the first term the learning algorithm does not observe the example z_i while in the second the term z_i is indeed observed. If the difference is very large, the learning algorithm might been overfitting

Ridge Regression

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- Ridge regression shrinks the coefficients towards 0, but does not lead to a ***sparse model***

Lasso

Lasso

$$\hat{\beta}_{lasso} = \arg\min_{\beta} ||y - \beta||_2^2 + \lambda ||\beta||_1$$

- It stands for *Least absolute shrinkage and selection operator*
- It replaces the ridge regularization term $\sum_{i=1}^{p} \beta_i^2$ with the sum of the absolute weights $\sum_{i=1}^{p} |\beta_i|$
- Thus, lasso uses L_1 regularization, whereas ridge regression uses the L_2 norm
- Lasso regression favors sparse solutions

Lasso

- It is quite sensitive to the regularization parameter λ, which is usually set on hold-out data or in cross-validation
- Therefore, there is no closed form solution and numerical optimization technique must be applied.

In summary...

- Ridge regression
  - correlated variables get similar weights
  - identical variables get identical weights
  - It is not sparse
- Lasso
  - correlated variables are randomly picked out
  - It is sparse

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